



NERD PUBLICATION

**INTERNATIONAL CONFERENCE ON
TRANSFORMATIVE RESEARCH
ICTR-2025**

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18 April,2025

ISBN:978-81-969383-4-5

New Era Research Development Publication
Pune, Maharastra
www.nerdpublication.com

About ICTR-2025

The International Conference on Transformative Research (ICTR-2025) is a focused online event scheduled for April 18, 2025, organized by NERD Publication. With a strong commitment to interdisciplinary dialogue and innovative thinking, ICTR-2025 provides a vibrant platform for researchers, scholars, and practitioners from across the globe to share cutting-edge research, explore new ideas, and build collaborative networks.

The core aim of ICTR-2025 is to drive transformative research that transcends traditional boundaries. The conference brings together leading voices from engineering, technology, health sciences, education, environment, social sciences, and management to foster impactful discussions and collaborative solutions to today's complex global issues.

Participants will engage in a rich program of keynote addresses, thematic sessions, panel discussions, and technical presentations, all designed to facilitate knowledge sharing, scholarly advancement, and academic networking.

This multidisciplinary forum promotes applied research and real-world innovation, offering attendees a unique opportunity to contribute to ongoing global development initiatives through academic excellence.

Vision

To advance transformative research that fosters innovation, interdisciplinary collaboration, and sustainable development in response to global challenges.

Mission

To provide a global platform for scholars, researchers, and professionals to exchange knowledge, present innovations, and promote multidisciplinary research across science, technology, health, education, and society.

Objectives

- Facilitate collaboration among academic and professional communities
- Promote cross-disciplinary research and innovation
- Address real-world challenges through scholarly exchange and applied solutions
- Disseminate quality research through indexed publications

Scope & Themes

The International Conference on Transformative Research (ICTR-2025) brings together a wide spectrum of disciplines to address emerging trends and critical issues across the following special tracks:

1. Special Track on Engineering & Technology

- **Emerging Technologies:** AI & Machine Learning, Cyber-Physical Systems, Robotics, Industry 4.0, Digital Twins, VR/AR
- **Sustainable Engineering & Innovations:** Renewable Energy, Green Technologies, Smart Cities, Circular Economy, Water Management

- **Computing & Data Science:** Big Data, HPC, Cloud/Edge Computing, Blockchain, IoT, Quantum Computing

2. Special Track on Medical, Health & Life Sciences

- **Biomedical & Healthcare Technologies:** Diagnostics, Telemedicine, Wearables, AI in Healthcare, Genomics
- **Public Health & Epidemiology:** Disease Prevention, Health Policy, Mental Health, Healthcare Systems
- **Pharma & Biotech Advances:** Nanomedicine, Biopharma, Genetic Engineering, Cancer Research

3. Special Track on Social Sciences, Management & Education

- **Business & Management:** Innovation, E-commerce, Sustainable Models, Leadership, Supply Chain
- **Education Innovations:** Digital Learning, STEM, Blended Learning, EdTech, Gamification
- **Society, Culture & Ethics:** Human Rights, Gender Studies, Political Science, Media, Legal Research

4. Special Track on Environmental & Natural Sciences

- **Climate Change & Sustainability:** Green Policies, Biodiversity, Disaster Resilience, Energy Transition
- **Applied & Natural Sciences:** Materials Science, Environmental Chemistry, Physics, Space Science

Editor-in-Chief
Dr. Sujatha K.
&
Prof. Venkateswara Rao

Keynote Speakers

1. **Dr. E. N. Ganesh**
Professor
Veltech Multitech Chennai

Title: Internet of Medical Things – Opportunities and Challenges

Abstract: The Internet of Medical Things (IoMT) refers to the interconnected network of medical devices, wearables, and other technology that can collect, transfer, and analyse health data. This technology is transforming the healthcare industry by enabling real-time patient monitoring, improved patient outcomes, and reduced costs. In this discussion, we'll take a closer look at what IoMT is, how it works, and its benefits to the healthcare industry. The Internet of Medical Things (IoMT) refers to a vast network of medical devices, wearables, and other technology that are connected to the Internet and can collect, transfer, and analyse health data. This data can be used to improve patient care and outcomes, reduce costs, and streamline healthcare operations. IoMT includes devices such as heart rate monitors, wearable fitness trackers, glucose meters, and smart pills, among others. The Internet of Medical Things (IoMT) works by collecting data from medical devices and wearables and transferring it to healthcare providers, such as doctors and hospitals. This data can be used to monitor patients in real-time and provide early warning signs of potential health problems. The data can also be analysed to identify patterns and trends, which can lead to improved patient outcomes and reduced costs. Benefits of using IOMT are

1. Improved Patient Outcomes
2. Cost Reduction
3. Increased Efficiency
4. Improved Patient Engagement
5. Better Decision Making

The IoMT improves patient outcomes by providing real-time monitoring of patients and enabling healthcare providers to detect health problems early and take prompt action. The IoMT reduces costs by reducing the need for frequent hospital visits and other medical procedures. By monitoring patients in real-time, healthcare providers can detect health problems early and take prompt action, leading to improved patient outcomes and reduced costs. Additionally, the IoMT can streamline healthcare operations by reducing the amount of manual data entry, which can help to reduce healthcare costs. IoMT comes with some unique legal, regulatory, technical, and privacy challenges, mainly because the IoMT ecosystem has so many stakeholders, including:

- Medical device providers
- Connectivity providers
- Original equipment manufacturers (OEM)

- Systems/software providers
- System integrators
- End users

2. Dr. P. Kamaraj

Professor and Dean

Bharath Institute of Higher Education and Research Chennai

Title: Hydrogen Generation and Sustainable Development

Abstract: In recent years, global climate change has been a major issue, because the energy production by combustion of fossil fuels has generated enormous amounts of greenhouse gases like NO_x, SO_x and CO₂. One of the best solutions for this issue is to replace the limited fossil fuels by hydrogen, because of its benefits such as environmentally friendly by-products and its fuel value is ~143 kJ g⁻¹. Cerium oxide has been extensively studied for photocatalytic applications, owing to its suitable band gap, good catalytic properties and less significant toxicity. CZTS/CeO₂-3 used in this study exhibits the highest H₂ production rate of 2930 μmol h⁻¹ g⁻¹, which is 59 and 48 times higher than those of bare CeO₂ and CZTS, respectively.

3. Dr. Inderbir Kaur Sandhu

Associate Professor

GSSDGS Khalsa College

Punjab

Title: *Technology and Pedagogy: Innovations in Higher Education*

Abstract:

“The illiterate of the 21st century will not be those who cannot read and write, but those who cannot learn, unlearn, and relearn.”

— Alvin Toffler

As higher education stands at the crossroads of technological disruption and pedagogical reform, university professors and academic professionals play a pivotal role in shaping the future of teaching and learning. This keynote speech explores the dynamic interplay between emerging technologies and evolving pedagogical frameworks, with a practical lens focused on real-world case studies and institutional innovations.

Highlighting successful implementations from leading universities worldwide, the address will examine how AI-powered learning analytics, flipped classrooms, immersive virtual environments, and micro-credentialing platforms are being effectively integrated into curricula. Case studies will include:

- **The University of Melbourne's** AI-supported feedback systems that enhance student engagement in large courses.

- **MIT's Hybrid Learning Lab**, showcasing blended learning models that preserve academic rigor while improving accessibility.
- **The University of Cape Town's** use of mobile learning tools to bridge the digital divide and expand outreach.

These examples will be contextualized within broader themes such as faculty readiness, curriculum redesign, digital equity, and assessment reform. The session will also address the ethical considerations and institutional strategies necessary to foster innovation without compromising academic integrity or inclusivity.

Drawing from impactful case studies of Indian higher education system, the address will showcase innovations such as:

- **IIT Madras's *Online BSc in Data Science***, an accessible, modular program redefining the reach of elite education.
- **Delhi University's** integration of **SWAYAM** and blended learning frameworks to scale high-quality teaching across institutions.
- **Christ University's** implementation of **OBE-aligned digital platforms**, enhancing curriculum delivery and outcome measurement.

Session Chairs

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Principal, Veltech Multitech, Tamil Nadu

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Rajendra Institute of Medical Sciences, Ranchi

23. Nikhil Kumar Goyal

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Proceedings of

International Conference on Transformative Research ICTR-2025

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ISBN: 978-81-969383-4-5

Published by:
NERD PUBLICATIONS
Pune, Maharashtra

International Conference on Transformative Research

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NERD PUBLICATION

Session 1: Inauguration_10 a.m.

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3	Keynote Speech	Dr. E. N. Ganesh Professor Veltech Multitech Chennai	Internet of Medical Things – Opportunities and Challenges
4	Keynote Speech	Dr. P. Kamaraj Professor and Dean Bharath Institute of Higher Education and Research Chennai	Hydrogen Generation and Sustainable Development
5	Keynote Speech	Dr. Inderbir Kaur Sandhu Associate Professor GSSDGS Khalsa College Punjab	AI-Driven Blended Learning: The Next Frontier in Indian Higher Education

Session 2: Dissemination of Research Findings_11 a.m.

Paper N	Name of an Author	Research Title	Session Chair
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2	S.P. Vasudha Priya G. Suneetha Bai K. Yamini S. Madhavi	Predictors of Occupational Stress, Attitude towards CCE of Primary School teachers	
3	Deepa Parameswaran	AI-Enhanced Handlooms: Scaling Handmade Textile Production for Sustainability, Economic Equity, and Climate Resilience	
4	Mustafa Yağci Ali Osman Özkan	Design of Smart Surface Cleaner for PV Panels and Investigation of the Performance of Cleaning	
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Preface

The *International Conference on Transformative Research (ICTR-2025)* serves as a pivotal platform for advancing groundbreaking research that redefines traditional boundaries and addresses the evolving challenges of our global society. As the need for impactful, cross-sectoral solutions grows, ICTR-2025 brings together a dynamic community of scholars, practitioners, and thought leaders committed to fostering meaningful change through interdisciplinary inquiry and innovation.

Transformative research is characterized by its ability to challenge established paradigms, drive systemic improvements, and create lasting societal impact. From reshaping public health strategies to redefining educational systems, and from reimagining energy futures to revolutionizing data governance, this conference explores how knowledge can be applied to real-world issues in creative and collaborative ways.

The rapid pace of technological advancement continues to be a catalyst for transformation. Innovations in artificial intelligence, quantum computing, digital ethics, and human-centered design are enabling new approaches to problem-solving and decision-making. ICTR-2025 offers a forum to examine how these tools can be harnessed not only for efficiency and growth but also for equity, sustainability, and resilience.

Health and well-being are central themes in transformative research, as interdisciplinary efforts between medicine, behavioural sciences, and technology generate novel frameworks for disease prevention, mental health care, and accessible treatment models. The integration of digital health platforms and community-based initiatives demonstrates how research can directly enhance quality of life across diverse populations.

Equally vital are contributions from the social sciences, education, and humanities, which illuminate the human dimensions of change. Research in these areas guides our understanding of societal dynamics, cultural identities, governance structures, and ethical responsibilities—elements that are critical to shaping inclusive and forward-thinking policies.

Environmental transformation is another core focus. The urgency of climate change, biodiversity loss, and sustainable development calls for collaborative action. From circular economy models to green infrastructure and smart resource management, ICTR-2025 invites bold ideas that address ecological challenges while promoting harmony between human progress and environmental stewardship.

Engineering, design, and applied sciences also play a central role in shaping the future. Through innovations in renewable technologies, smart cities, and advanced manufacturing, these disciplines contribute to creating adaptive systems capable of responding to the complex needs of the modern world.

ICTR-2025 is a space where disciplines converge and innovation thrives. It embodies the belief that research, when conducted with purpose and in collaboration, can be a powerful force for transformation. We are grateful to all contributors—researchers, speakers, reviewers, and organizers—whose commitment and vision have made this event possible.

Welcome to ICTR-2025 – where transformative ideas lead to transformative impact.

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3	AI-Enhanced Handlooms: Scaling Handmade Textile Production for Sustainability, Economic Equity, and Climate Resilience	Dr. Deepa Parameswaran
4	Design of Smart Surface Cleaner for PV Panels and Investigation of the Performance of Cleaning	Mustafa Yağci Ali Osman Özkan
5	Influence of Personal Causes of Low Achievers on Perceptions Towards Their Low Achievement in Biological Science	K. Yamini Prof. G. Suneetha Bai S.P. Vasudhapriya S. Madhavi
6	Enhanced CBAM-Efficient Net Model for Efficient Tuberculosis Diagnosis Using Chest X-Ray Images	Prof. Dangete Suma Malladi Sneha Mohammad Shafi Shaik Subhani Anabathula Mohith

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Analyzing Various Machine Learning Classifiers for the efficient Prediction of Student Mental Stress

Abstract

A prevalent societal issue that affects people nowadays is mental stress. Stress is typically felt when one feels that the amount of pressure or demand is more than one's ability to handle it. A person's thoughts, actions, emotions, and interpersonal communication can all be impacted by mental health problems. The major issues that student faces now a days that will suffer their mental health are Depression, Addiction, Anxiety, Eating Disorders, Substance Misuse and Suicidal Intent. Some Students also suffers from a Huge Academic Pressure. It might be from their own mind for gaining more & more in their Academics or might be from Parental Pressure. Accurate analysis and prediction of stress patterns may be possible with the use of machine learning techniques and enabling prompt responses. With an emphasis on the function of machine learning models, the influence of physiological and behavioural characteristics, this paper explores the important facets of mental stress detection. The search was conducted on several databases (IEEE, Scopus, Elsevier, and Web of Science). The topmost objective of the paper is to analyze various algorithms that are used to predict the level of stress among an individual. This Review paper is based on the analysis of various approaches and finally gives the most appealing among all. Random Forest & Gradient Boosting are the best algorithm with topmost accuracy that has been used in various papers and also helps in accurately predicting the level of stress among the individual.

Keywords: K Nearest Neighbor, Random Forest, Naïve Bayes, Regression, Decision Tree, Support vector machine, Gradient Boosting

1. Introduction

Anything that triggers a physiological response, whether internal or external, is considered stress. Stress is any exogenous or innate stimulation which causes a reaction to the body. Stress is typically felt when one feels that the amount of pressure or demand is more than one's ability to handle it. The item that stresses us out is known as a stressor because it grabs our attention and results in an emotional and physical response.

A stress reaction is a unique response, and what could be stressful for one person may be different for another. The type and intensity of a stress reaction also differ from person to person. Many different things might cause stress, such as a job that you can't finish or aren't qualified or prepared to accomplish, financial difficulties, personal and family health issues, workload and ability to handle it, etc. Even joyous occasions like holidays, weddings, and relocation may be stressful. A prevalent societal issue that affects people nowadays is mental stress. Stress decreases human performance at ordinary tasks and may cause serious health problems. According to research, 60% of college students experience anxiety, indicating the need to increase mental health services by 30% to 40%. Moreover, findings indicate that Students reported from mild to extreme stress in 88% of cases, from mild to extreme anxiety in 44%, and from mild to extreme depression in 36% of cases [1].

Based on these traits, one could assume that, despite its difficulties, their time in school would be one of well-being, contentment, and personal growth. Regrettably, research indicates that the existing educational system may unintentionally harm student mental health, as worry, stress, and sadness are very common. There is a heavy body of evidence that shows how stress affects both the physical and mental health, and that the right amount of stress improves learning while too much stress causes health problems. Workload, lack of sleep, financial worries, academic pressure, student abuse, and a covert cynical curriculum are some of the theories put out to explain this downturn in student mental health. Academic performance of students may suffer from stress, which can also lead to academic dishonesty and drug and alcohol abuse. Distress among students has also been linked to cynicism and a lack of concern, which kills empathy the foundational quality of humanity.

Nomenclature:

AB: Adaptive Boosting **LR:** Linear Regression **DT:** Decision Tree
RF: Random Forest **XG:** eXtreme Gradient Boosting **KNN:** K-Nearest Neighbor
NB: Naive-Bayes **SVM:** Support Vector Machine

2. Importance of Early Detection of Stress

Academic stress is another name for the stress that students experience. Worry resulting from education and schooling is known as academic stress. Acquiring a degree and furthering one's education can frequently entail significant strain. Managing time, finding time for extracurricular activities, and finishing all the work can be stressful. In various professions and activities, stress and its symptoms, including depression, anxiety & burnout as a prevalent issue. Concern has been aroused

in the past few decades by the increasing number of workshops that are organized to help people deal with this condition, as well as the profiling of books, popular articles and research studies. In modern hectic life the stress is a great menace. The most unsatisfactory thing in modern life is that man is so busy with external matters that he has no time for himself. In the same way students are too busy with their work. They are preoccupied with their studies. They take a lot of stress of their work. So it is important to detect the stress in students at the earliest so that they can change their daily routine which will be beneficial for their future life.

3. Signs and Symptoms of recognizing stress in yourself and others

In the fields of education and industry, stress detection is crucial for evaluating the effectiveness of instruction, making educational improvements, and lowering the possibility of human error brought on by stressful work environments. As a result, early mental health diagnosis is crucial to preventing disease and other health issues. Numerous physical, behavioral, and/or psychological symptoms can be signs of stress. Common signs & symptoms include:

1. **Physical symptoms** include headaches & Migraines, insomnia, nausea, increased heart rate and blood pressure, sobbing fits, sleep disturbances, aches and pains in the muscles, fatigue, a higher risk of infection and a rise in cold and flu-like illnesses, gastrointestinal issues etc.
2. **Behavioural issues** include difficulty focusing, forgetfulness, irritability, substance abuse (such as increased use of alcohol, coffee, or tobacco), changes in eating habits, tardiness, a rise in absenteeism, poor work performance, fidgeting, an inability to perform well at work despite well-laid plans, and withdrawal from regular social interactions.
3. **Psychological symptoms** include depression, misdirected anxiety, apathy, irritability and anger, difficulty focusing and remembering details, low self-esteem, fear of failing, and unusual behaviour.

4. Applications of Stress detection for students

Machine learning (ML)-based stress detection systems are revolutionizing the way that mental health issues among students are handled in educational settings. Students' stress levels are greatly increased by the demanding requirements of their coursework, extracurricular activities, peer connections, and career planning. The following are some ways that using ML-powered stress detection systems can offer customized solutions and enhance wellbeing:

1. Tracking Academic Stress

By examining behavioral and physiological data, stress detection devices assist in identifying students who experience difficulties with academic demands or exam pressure.

- To recommend adaptive learning techniques, machine learning models such as support vector machines (SVMs) examine performance data, study schedules, and sleep patterns.
- Before students experience burnout, early stress detection can lead to counseling sessions or relaxation exercises.

2. Programs for Mental Health and Wellbeing

Stress detection systems can assist educational institutions in establishing successful mental health initiatives by evaluating data from wearables or self-reported measures.

- By identifying patterns of social disengagement, anxiety, or depression, logistic regression models allow counselors to intervene in real time
- Based on insights from machine learning models like decision trees, suggestions for stress-relieving exercises like yoga or art therapy are made.

3. Enhanced Peer and Teacher Relationships

By locating the causes of relational stress, stress detection systems can enhance the relationships between students, teachers, and peers.

- Machine learning algorithms can identify bullying trends or communication breakdowns by examining text or audio data.
- By giving teachers feedback on how their methods impact students' stress levels, systems allow for modifications.

4. Career Guidance and Assistance with Decision Making

Uncertainty about their careers causes stress for many students. When paired with machine learning, stress detection systems can offer recommendations based on a student's preferences, strong points, and stressors.

- Making stress-free recommendations for professions or academic programs that play to a student's strengths.
- A real-time assessment of the efficacy of career training or counseling sessions.

5. Mitigation of Peer Pressure and Bullying

In order to identify kids who are being bullied or pressured by their peers, machine learning (ML)-based stress detection systems can examine contextual and behavioral data.

- Systems can assist in developing focused interventions for students who are at danger.
- Workshops and programs that teach kids how to deal with peer pressure are designed using insights from machine learning models.

6. Real-Time Feedback and Alerts

Stress detection systems that use real-time data analysis can notify parents or school officials about pupils' critical stress levels.

- Warning signs of extreme stress that allow for prompt medical attention.
- guiding modifications to policies, such cutting back on homework or rearranging class schedules.

5. Methodology

Search Strategy and Data Collection

A systematic and thorough approach was used in the methodology for this review in order to find, collect, and evaluate pertinent research papers and data on mental stress detection, with an emphasis on the incorporation of machine learning techniques. The search approach was created to cover a

broad spectrum of interdisciplinary materials, guaranteeing the inclusion of research from a number of fields, such as computer science, psychology, and the medical sciences.

1. Search Approach

Several scholarly databases, including ScienceDirect, PubMed, IEEE Xplore, SpringerLink, Scopus, and Google Scholar, were used in the literature search. The following terms and phrases were used because they were pertinent to the research topic:

- "mental stress detection,"
- "machine learning and stress,"
- "physiological parameters in stress detection,"
- "ensemble learning techniques," and
- "wearable devices for stress monitoring."

In order to ensure that studies addressing physiological, behavioral, and contextual aspects in stress detection were included, boolean operators (AND, OR) were used to refine search results. To ensure accuracy and relevance, the search was restricted to papers released in peer-reviewed journals, conference proceedings, and reliable open-access platforms during the last ten years. Priority was given to articles that made substantial methodological or technical contributions.

2. Inclusion and Exclusion Criteria

- **Inclusion Criteria:**

Studies focusing on physiological and behavioral parameters for stress detection, and reviews summarizing existing methodologies and challenges. Papers employing multi-modal datasets and ensemble learning techniques were given priority to align with the study's objectives.

- **Exclusion Criteria:**

Studies without empirical evidence, papers in non-English languages, and articles focused on unrelated stress concepts (e.g., financial or ecological stress).

3. Data Collection

The collected data encompassed parameters (e.g., heart rate variability, blood pressure, respiratory rate) and behavioral indicators (e.g., sleep quality, activity levels, and academic workload). The main focus was given on studies these parameters with machine learning models, including logistic regression, support vector machines, decision trees, and gradient boosting. Additionally, ensemble learning techniques like random forests and AdaBoost were explored for their robustness in handling noisy and imbalanced datasets. Data from wearables and smart devices, such as ECG and GSR sensors, were particularly highlighted due to their practical applications in real-time stress monitoring.

4. Review and Analysis

All identified studies were subjected to rigorous screening and critical analysis. The extracted data were synthesized to assess trends, strengths, and limitations of various methodologies. Special

attention was given to the scalability, accuracy, and real-world applicability of machine learning models in stress detection.

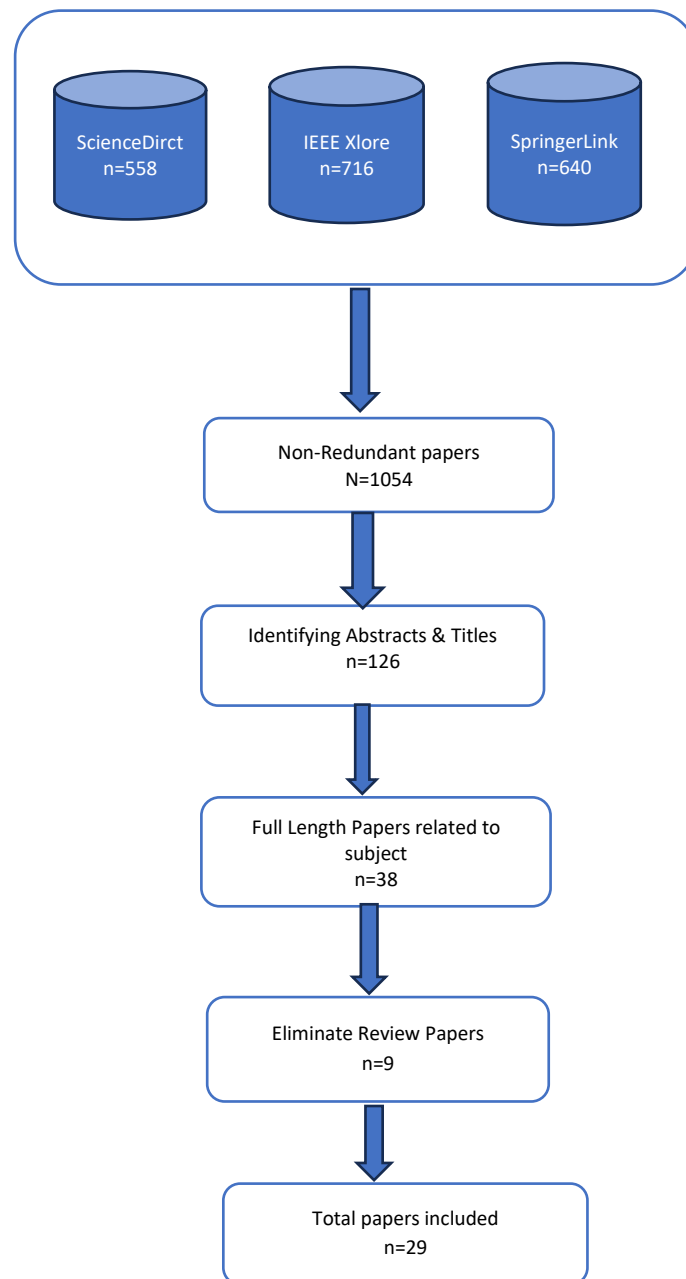


Fig 1: The flowchart elaborates the strategy for search used for the review paper

4. Challenges and Ethical Considerations

Ethical concerns, including data privacy and the interpretability of machine learning models, were documented. Future research directions were identified based on gaps and limitations observed in the existing literature.

1) Literature Review

TABLE 1: Literature review and Overview of Recent Studies on Stress level Prediction Using machine learning classifiers

Sn o	Author Reference	Year	Journal / Publisher Name	Dataset Used	Algorithms and Techniques Used	Results	Conclusion
1	[2]	2024	Elsevier	SWEET dataset of 240 healthy adult volunteers	K-Nearest Neighbors (KNN), Decision Tree (DT), Support vector classification (SVC), and Random Forest (RF)	RF gives 93.58 accuracy, DT performs 94.61, SVC gives 96.27 and KNN performs 98.44 of accuracy	KNN performs superior as compare with with SVC, DT and RF
2	[3]	2023	Elsevier	127 Students of Engineering	Random forest, Naïve Bayes, Decision tree and Support vector machine algorithms	Random Forest gives accuracy as 78.9%, Naïve Bayes as 71.05%, SVM as 75.5% and Decision Tree as 71.05%	The best accuracy obtained from Random Forest i.e 78.9%
3	[4]	2023	Elsevier Journal of Biomedical Informatics	Dataset of 90 Participants taken	Random forests, Support vector machines & gradient boosting models	Light GBM gives an F1 value of low Perceived Stress is 0.776, AUC is 0.741, Precision of 0.726	The Gradient Boosting model gives the best result
4	[5]	2022	Research Square	15,366 university	Bagging, k-nearest	Random forest has	Adaptive boosting &

				Students with 20 factors	neighbor, Neural networks, Generalised linear models, random forest, naïve-Bayes & boosting algorithms	accuracy 0.921, KNN gives accuracy as 0.775, Adaptive Boosting gives 0.893, and naïve-Bayes as 0.723	Random forest algorithms achieved the topmost accuracy
5	[6]	2022	Hindawi	Historical data of 5 Years dataset of 1036 Students	Back Propagation Algorithm	The difference between Predicted and measured is 0.88%	The prediction model of the Back Propagation neural network avoids the tedious Traditional process of modeling
6	[7]	2022	AICECS Journal of Physics: Conference Series	A dataset of 1259 Entries with 27 attributes was taken	Decision Tree, K-NN Logistic Regression, Stacking & Random Forest	The Technique of Stacking achieved a Prediction accuracy of 81.75%. KNN, RF and SVM equally performed	The mean accuracy of all the classifiers is 79%.
7	[8]	2022	Hindawi Scientific Programming	A dataset of 280 undergraduate students	K means Clustering, NaïveBayes, Random forest, decision tree & BP Neural Network	According to experimental findings, mental health issues are recognized in 75% of students.	The decision Tree is best among five as it gives F1-measure 0.69, Recall 0.58 & precision 0.68

8	[9]	2022	Frontiers in Public Health	Time-series data on the COVID-19 pandemic's daily OPHS number were gathered in 2020.	The model consists of Random forest, LR, Ridge, LASSO, SVR	The mean Predictive Performance of LR is 25.945, Ridge 6.440, LASSO 8.307, SVR 6.018, RF 6.280	The OPHS value is 29.929 on a daily average.
9	[10]	2022	Rochester Institute of Technology, Rochester, New York	A dataset of 270 Participants had been collected from surveys & Structured Questionnaire	Two algorithms used in it SVM and RF	Performance evaluation was measured based on accuracy, precision, and recall	SVM gives better output at 80.2%
10	[11]	2022	Springer, Natural Medicine	The dataset is based on data of EHR 7 years (2012–2018) from 17,122 patients.	Deep learning-based classifiers, decision trees, and probabilistic ensembles	<i>XGBoost</i> Obtained ROC as 0.797, Precision 0.159, sensitivity 58% & specificity 85%	The most effective overall performance was shown by XGBoost.
11	[12]	2022	Tech Science Press	Dataset of adults between 2005 and 2018	LR, Elastic Net, RF, Extremely Randomized Trees Classifier, XGBoost, Linear SVM, Polynomial SVM	Random Forest (RF) gives 91% and Extra Tree Classifier gives 92%	The loss function has been optimized using the Frequent Model Retraining (FMR)& Ensemble Learning Approach (ELA)

12	[13]	2022	International Research Journal of Modernization Engineering Technology and Science	The dataset has been imported from the Excel file	KNN, Naïve Bayes, Decision Trees, Boosting	The visual GUI Based system produced an accuracy of 87%	KNN and Boosting produced the highest accuracy
13	[14]	2021	International Journal of Perceptive & Cognitive Computings	The dataset of 219 university students for the year 2021 from India was acquired from Kaggle.	K-Nearest Neighbors, Naïve Bayes Decision Tree & Support Vector Machine are used in it.	Decision Trees has an accuracy of 0.64, KNN of 0.59, and SVM as 0.44	Decision Trees perform better
14	[15]	2021	Journal of Health, Population & Nutrition	355 Students from 28 different Bangladesh university using a questionnaire .	DT, RF, SVM, K-fold validation techniques.	DT has Macc(Mean of Accuracy scores) 0.8870, RF 0.8983, SVM (polynomial kernel) 0.7855, SVM (linear kernel) 0.8309, LR 0.7713 for 10 Fold	Random Forest Model has the highest accuracy
15	[16]	2021	Firouzabad Institute of Higher Education, Firouzabad, Fars, Iran	Twitter, Facebook, Biosensors, Students, SNS Post Dataset	SVM, Naïve Bayesian classifier	SVM is widely used in the health domain. ML Shows weak performance in large samples	Naive Bayesian shows high accuracy in sentiment analysis of Facebook status

16	[17]	2021	Frontiers in Public Health	Dataset of 5,108 Chinese medical professionals based on 32 criteria	Binary Bat, Stepwise logistic regression, hybrid improved dragonfly algorithm	The proposed model gives 92.55% prediction accuracy.	The IGCBABPNN model of prediction can obtain better output results in the prediction of mental health
17	[18]	2021	International Journal of Engineering Research & Technology	Dataset of 91 students by using Binning method.	KNN Classification algorithm used in it	The model obtained an Accuracy of 94.5054945054945%	The student can incorporate the work and solution towards maintaining his or her mental balance.
18	[19]	2021	scientific Report Nature Research	4284 UG Students for MDD and GAD	Logistic Regression, SVM, Random Forest, XG Boost, K Nearest neighbor & Neural Network algorithms	For GAD the values of AUC is 0.73(Specificity 0.7, sensitivity:0.66) & for MDD the values of AUC is 0.67(sensitivity:0.55, Specificity 0.7)	The positive & negative predictive value was 16% and 96%
19	[20]	2021	European Journal of Medical and Health Science	Dataset of 30 final-year medical students including 19 males & 11 females	Average pre and post-test scores	Findings showed that the test group's average percentage coherence score was substantially greater ($p < 0.05$) than the control	When compared to before the exam, when exam takers were showing signs of stress, the coherence score was

						groups in the lowest cardiac coherence domain but lower ($p < 0.05$) in the highest coherence domain.	significantly higher ($p < 0.05$) after the examination, indicating release from stress.
20	[21]	2021	IEEE	A dataset of 60 sample data points based on pulse rate, GSR, and skin temperature is taken	LR, SVM, NB, RF, DT and ANN approaches are used.	LR achieves 90%, KNN 83% NB 87%, SVM 85%, RF 79% accuracy	ANFIS-FWGWO classification algorithm performs with an accuracy of 94%
21	[22]	2020	Springer	Dataset of 6630 Children of 2013-17	Classification and Regression tree Analysis Algorithm, Deep Multi-layer neural networks, Logistic Regression.	Regression tree analysis has AUC=.68, logistic regression model AUC=0.69, deep multi-layer NN AUC = .72, Ensemble model AUC=.71,	A Deep multi-layer NN with AUC=0.70 has Maximum Accuracy
22	[23]	2020	IEEE University College London	Dataset Collected from DDI (data Driven Investor) with a group of 752.	Logistic Regression, KNN, SVM, Naive Bayes, Decision Trees	The result shows Depressed Students are 135 in number	To determine whether a certain twist is depressive or not, Twitter scraping tool Twint is used in it.

23	[24]	2020	PLOS National University of Science and Technology	7,638 twins were included in the children and adolescent twin study.	XGBoost, Logistic Regression, Neural Network, Random Forest, SVM	RF AUC = 0.739, 95% CI, SVM (AUC = 0.735, 95%	Logistic Regression has the best AUC 0.750
24	[25]	2020	International Journal Education & Management Engg	Analysis of Factors Affecting Mental Health resulting lack of financial and social support	Decision tree, SVM, and neural network	With a score of more than 70%, these three are extremely accurate.	SVM achieved the highest accuracy between 70% to 96%
25	[26]	2020	IEEE	WESAD Dataset is used.	Linear Discriminant Analysis, K-Nearest Neighbour, Random Forest, Decision Tree, Kernel Support Vector and AdaBoost	Machine Learning techniques gives Accuracy of 81.65% and 93.20% on a three-class and binary classification problem	The achieved accuracy ranges from 84.32% and 95.21%
26	[27]	2020	International Journal of Mechanical and Production Engineering Research	The dataset of 200 university students was collected using PSS Scale,	Linear Regression, Naive Bayes, Random Forest, Multi-Layer Perceptron,	Bayes net gives accuracy as 88.59%, Multilayer Perceptron as 85.43%, Naive Bayes as	Bayes Net Classifier give the maximum Accuracy at 88.5965%

			Development	ADULT ADHD Self-Report Scale and Weka Tool	Bayes Net, and J48 algorithms used	84.2105%, Logistic Regression 84.9649, J48 gives 86.42, Random Forest 83.333%	
27	[28]	2020	International Journal of Engineering and Advanced Technologies	A dataset of 220 UG and PG was collected by using PSS Scale through google dox	SVM, KNN, RF, Naive Bayes, Logistic Regression, Decision Tree	Bayes net gives accuracy as 88.59%, Multilayer Perceptron as 85.43%, Naive Bayes as 84.2105%, Logistic Regression 84.9649, J48 gives 86.42, Random Forest 83.333%	Baye's Net classifier produces the highest 88% of accuracy.

7. Findings and discussions

The integration of machine learning (ML) into stress detection has opened new possibilities for understanding and managing mental health challenges in diverse environments. This study explored the applications of stress detection technologies in driving conditions and academic environments, highlighting their potential to enhance safety and well-being. However, the adoption of these technologies is not without its challenges, including data privacy, ethical considerations, and individual variability in stress responses.

1. Effectiveness of ML in Stress Detection

By analyzing physiological parameters such as heart rate variability (HRV), electrodermal activity (EDA), and respiratory rate, ML models have shown robust performance across different scenarios. Behavioral indicators, including driving patterns and academic workload, further enhance these models' predictive capabilities when combined with physiological data.

2. Real-Time Monitoring and Interventions

The implementation of real-time stress monitoring systems has proven particularly effective in dynamic environments such as driving and academics. For drivers, real-time alerts based

on physiological data can prevent accidents by encouraging breaks or activating automated driving modes. Similarly, in academic settings, real-time feedback allows students to manage stress during high-pressure situations, such as exams or deadlines.

3. Challenges in Implementation

Despite promising results, stress detection systems face several hurdles:

- **Data Privacy:** Continuous monitoring involves collecting sensitive physiological and behavioral data, raising concerns about data security and misuse.
- **False Positives and Accuracy:** Ensuring high precision in stress detection is crucial to avoid unnecessary interventions, which may cause further distress.
- **Adaptability:** Stress responses vary across individuals due to genetic, cultural, and situational factors. Models must account for these differences to provide personalized solutions.
- **Resource Constraints:** Implementing wearable devices and monitoring systems on a large scale can be cost-prohibitive, particularly in educational institutions.

4. Ethical Considerations

The ethical implications of stress detection systems are profound. While these technologies can improve well-being, they also pose risks of surveillance and misuse. Ethical frameworks must guide their development to ensure they prioritize user consent, transparency, and inclusivity

Based on Literature Review which is done of papers from 2020-2024, we find that SVM & Random Forest algorithm are best among all techniques. More than 25 research papers were reviewed of recent years. These papers showed some important and relevant details of the algorithm were included in literature review. Supervised machine learning algorithms are applied for Stress level Prediction.

8. Conclusion

To conclude, we can say the Stress has major detrimental effects on both academic and physical. It results from poor nutrition poor sleeping habits, unhealthy eating habits and academic pressure. All the efforts of both the educators and parents to make ensure that student do not feel a great deal of tension. This study highlights how machine learning can revolutionize stress detection in a variety of settings. By offering individualized support and facilitating stress-free learning environments, these tools help students in academic contexts deal with mental health issues. The results show that the best outcomes for stress detection come from combining behavioral and physiological data. When compared to single-feature models, multi-modal systems—which incorporate data from wearables, in-car sensors, and academic tracking tools—perform better. Additionally, by using ensemble learning approaches, predictions become more robust and generalizable, which makes these systems suitable for practical uses. By Reviewing above mentioned papers, we concluded that Ensemble

learning techniques, which combine the predictions of multiple base models, have shown superior performance in stress detection tasks. Methods like random forests, AdaBoost, and gradient boosting have been applied to improve the robustness and accuracy of predictions. By aggregating the strengths of individual models, ensemble methods reduce overfitting and enhance generalizability, making them particularly effective in handling noisy and imbalanced datasets common in stress detection research. For instance, gradient boosting has proven effective in capturing non-linear relationships between features, such as the interplay between mental health history and academic performance in stress prediction. SVM, Random Forest algorithm, Gradient Boosting & Decision Tree are best among all techniques. To be more precise Gradient Boosting & Random Forest are the best algorithms that have been used in various papers and also help in accurately predicting the level of stress among an individual. The potential effects of this psychological issue on students' health, academic achievement, and ability to advance in their professional lives make it extremely dangerous. The three most prevalent factors - a poor learning environment, a lack of social support, and financial difficulties have been identified. Furthermore, the scope of this issue must be recognised and comprehended. To identify the research gaps, several research publications have been compared. The investigation of predictors of receiving psychosocial treatment was aided by machine learning models. To get predictive performance, further data and data pre-processing methods should be investigated for other models.

Future Directions

Technologies for stress detection are revolutionizing the way mental health issues are handled. These systems provide promising solutions for improving well-being, productivity, and safety in a variety of settings by utilizing machine learning and sophisticated data collection techniques. But in order to reach their full potential, a concentrated effort is needed to solve existing constraints, guarantee moral application, and promote interdisciplinary cooperation. Stress detection systems will improve in accuracy, accessibility, and impact as technology advances, fostering a society that is healthier and more robust.

- Future studies should examine stress detection in various contexts, such as workplaces, healthcare facilities, and sports, even though this study concentrated on academic settings. Future initiatives should concentrate on making sure systems are impartial and inclusive, as well as expanding datasets to encompass a variety of demographic groupings. utilizing multi-modal datasets, which include environmental, behavioral, and physiological data by improving methods for preparing data in order to reduce noise and increase signal clarity.
- Individualistic stress reactions are a result of a variety of factors, including personality, life experiences, and heredity. Adaptive algorithms that learn from unique patterns and offer customized interventions should be a part of future systems. Real-time personalization may

be made possible by methods like deep learning and reinforcement learning, which would improve user effectiveness and experience.

- Advanced anonymization approaches can preserve the usefulness of stress data for analysis while safeguarding user privacy.
- ML and AI-powered virtual assistants working together could give consumers dynamic, situation-specific stress-reduction techniques. AI systems might, for instance, suggest customized relaxation techniques based on past data and present stress levels.

Author's contributions: Each author contributes significantly to the manuscript's writing.

Competing Interest: The authors declare that they have no competing interests.

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Predictors of Occupational Stress, Attitude towards CCE of Primary School Teachers

Abstract:

Globalization has made a tremendous impact on all spheres of life and education is no exception. The growing demand for globalization raises a lot of changes in education on the quality of education. To meet these growing demands a lot of changes are being made in the field of education and one such change is evaluation. The main objective of the present study is to find out the predictors of Attitude towards CCE and occupational stress of Primary school teachers. Teachers' attitude Scale, Occupational stress scale was adopted. A sample of 800 primary school teachers representing different management and locality in Warangal District is taken for the data analysis following stratified sampling technique. The multiple regression test was employed for analysis of the data.

Key words: Occupational Stress, Continuous and Comprehensive Evaluation, Attitude and Primary School Teachers.

Introduction

Education is a comprehensive and multifaceted process activity aimed at cultivating specific goals such as intellectual, emotional, social and physical development, preparing individuals to live in an ever-changing world. These goals may include enhancing understanding, reasoning, kindness and integrity. Education can also refer to the mental states and dispositions of educated individuals rather than the educational process itself. Originally intended to pass on cultural heritage to future generations, modern educational objectives now encompass new ideas such as learner empowerment, contemporary social skills, empathy and advanced vocational abilities. In the context of education, evaluation is often used to assess student learning outcomes, teacher effectiveness and the overall influence of educational programs and initiatives (Stufflebeam, 2003). For example, an evaluation of a new teaching strategy might involve gathering data on student performance, teacher attitudes and perceptions and classroom observations (Darling-Hammond and Bransford, 2005). The results of the evaluation could be used to refine the teaching strategy and improve student learning outcomes. Overall, evaluation is an important tool for ensuring that programs and policies are achieving their intended goals and for identifying opportunities for improvement. By gathering and analyzing data on the effectiveness and influence of interventions, decision-makers can make informed choices and allocate resources more effectively (Patton, 2018).

Continuous and Comprehensive Evaluation (CCE) Continuous and Comprehensive Evaluation (CCE) is an assessment system used in many schools in India. The CCE system was introduced by the Central Board of Secondary Education (CBSE) to replace the traditional examination-based assessment system. The primary objective of the CCE system is to provide a more holistic approach to student assessment by evaluating them continuously throughout the year on a range of parameters, rather than relying solely on a single, high-stakes exam at the end of the academic year. The CCE system has been widely adopted in India, although it has also been subject to some criticism. Critics argue that the system places too much emphasis on continuous assessment, leading to a culture of constant testing and pressure on students to perform well in every assessment. Others argue that the system can be too subjective, with teachers having too much discretion in evaluating students. The Right to Free and Compulsory Education Act of 2009 established the right to free and compulsory education as a basic right. To chart student's progress in this direction, learning outcomes for several subject areas up to the elementary school level have been found. In addition to assisting teachers in directing their teaching-learning in the desired direction, the learning outcomes for each class also serve to make other stakeholders—particularly parents and guardians aside from School Management Committee members, the community and state functionaries—responsible and aware of their roles in ensuring quality education in the classroom. Therefore, the learning outcomes that are

explicitly stated can direct and ensure that many stakeholders have a responsibility and accountability to fulfil the expectations in various curricular areas (NCERT, 2017).

Acknowledging learning is an ongoing process to fill horizontal and vertical gaps that require planning, execution, modifications in teaching-learning by both teachers and students in a continuous process. CCE is integration of teaching-learning process and assessment in a cyclic manner. CCE requires collecting information from a variety of sources and using different ways of assessment in order to know and understand whether each child is actually learning while going through a variety of experiences, activities and learning tasks. Understanding that every child has a unique way of learning at a different level and also learning is not only happening in schools and with textbooks, Child-centered teaching-learning process and assessment strategies are essentially adopted in classrooms. In the classrooms teacher has to create a fear-free environment, where child can able to express freely, trust on their teacher and is able to share their likes, dislikes or problems without nervousness

The teacher should adopt a solution focused approach, working with parents, guardians and other colleagues to solve students' issues. If any physical, emotional issues faced by students or identified by teachers take the support of psychologists, cancellers or doctors. For gifted children or especially abled children, children with special needs (CWSN) teachers show more concentration and focus to make them busy for better achievements and to reach prescribed learning outcomes according to their level. Teachers have to provide material, aids, books, and adequate space for children who are available including those with special accommodations to suit the needs of all children.

CCE assessment is conducted in many ways such as self-assessment-peer assessment, individual-group activities, oral-written form, questioning, drawings, forming hypothesis, reflections, reactions, writing conversations and in many other ways. After finding the gaps, the teacher interprets the levels of students and communicates with them, then plans to fill the gaps. Teachers create opportunities in different ways such as peer group learning, individual learning, class room teaching, lab activities, multi-level group learning. With CCE teachers get a clear idea about students. It also helps the teachers to frame a fair idea of what children know and do not know.

To improve their learning, the teachers need to design and plan different learning tasks, which consider the contexts and learning needs of all children. It helps as it gives an individual planning for each child to participate with. CCE provides scope to the teachers to develop tentative, flexible day-wise plans. All these plans, especially the day-wise planning cannot be rigid but it needs to be flexible as sometimes, even question, response from children may require the teacher to change/modify her teaching-learning.

Role of Teacher in Improving Quality through CCE

When using the CCE approach in school, the teacher is crucial in bringing about the desired improvements. The foundation of CCE is the idea that since teachers know their students best, it is only appropriate to entrust them with the evaluation of the learner. This gives teachers the chance to regularly diagnose learning disabilities and implement remedial measures. In order to arrive at the right decision and make judgments, it requires analysis and interpretation of evidence of achievement. Students are evaluated based on specific competencies in each topic. A teacher can help students by using a variety of methods (oral, projects and presentations), comprehending varied learning styles and skills, sharing evaluation criteria with students, allowing peer and self-assessment and allowing students to improve. Thus, CCE is useful for a classroom teacher in the following ways:

Attitude

Attitude is an “enduring motivational, emotional, perceptual and cognitive process concerning aspects of the individual’s world” (Kerch and Crutchfield, 1948).

The fundamental concept of attitude is one of readiness or, taken literally, our position as people. It is a tendency for some people to perceive, feel, or behave in a certain way toward particular objects. A person’s attitude refers to how they act and behave towards things, individuals, institutions and events. Positive attitudes are linked to pleasant emotions. Contrarily, negative attitudes are connected to avoidance and withdrawal. Unsatisfactory attitudes are not readily observable but are reflected in observable behavior. Approach and avoidance tendencies can both be indicators of attitude and can be seen in what children do or say.

Attitude towards CCE

Attitude is a condition of readiness for a certain type of activity. Attitude denotes the inner feeling or belief of a person towards specific phenomena. Attitudes are dynamic, so they change with time and experience. Attitude of teachers towards CCE system may be defined as a positive or negative evaluation or liking and disliking about CCE system. The development of attitudes of teachers seems to be a major concern today. This is often approached as a problem of developing the effect. Attitudes involve the intellect and our perspective on things. Teachers need a positive attitude and an understanding of the components of CCE. Through understanding, teacher’s attitudes towards CCE can be developed. Attitude influences one’s behavior, inner mood and therefore evaluation. So, there is a connection between attitude and Implementation of CCE in which the teacher must develop. Positive attitude has a strong influence on the success of CCE. The attitude of an individual depends heavily upon different stimuli. A positive attitude results in a positive approach towards the subject/topic etc. Attitudes develop on the ABC model (affect, behavioral change and cognition). The affective response is a physiological response that expresses an individual’s preference for an entity.

The behavioral intention is a verbal indication of the intention of an individual. Teachers can also be ambivalent towards CCE, meaning that they simultaneously possess a positive and a negative bias towards the attitude in question to study the attitudes of teachers towards CCE. The study assessed differences in attitude change towards CCE. Attitude is the predisposition of an individual to evaluate some aspect of his world in a favourable or unfavorable manner. The aspect of his world that he evaluates includes symbols, objects, ideas and people. In the present study, the attitude of teachers towards the CCE system is defined as the sum of their inclination and feeling, prejudice and bias, ideas and convictions about a particular aspect related to the CCE system, i.e., the perception, thinking and feeling of teachers towards CCE. By this definition, the scope of the attitude study is limited to teachers' attitudes regarding specific objects and events related to the CCE system.

Teachers' Occupational stress

Stress is the "wear and tear" our bodies endure as well as how we adapt to our constantly changing surroundings. Stress causes physical and mental consequences on us and can elicit both positive and bad emotions. Economic, political, social, cultural, or educational organizations all experience emotional and social interactions that can lead to stress. It is a natural and unavoidable aspect of existence that cannot be denied.

In today's world of rapid industrialization and growing urbanization, stress is unavoidable in human life. It is a psychophysical state that has an influence on a person's capacity for work, efficacy and quality of life. When employees perceive their resources and ability to meet these expectations are out of balance, stress results. That is what derives from workplace conditions. Being unable to handle work pressures causes Teachers' stress. Teachers' stress leads to Teachers' health issues and is a significant cause of economic loss. Teacher stress is a specific type of stress. It is the experience of negative feelings by a teacher that are brought on by components of their job as teachers, such as tension, irritation, rage and depression. Teachers' stress may have an influence on psychological well-being, lower job satisfaction and personal wellbeing. When Teachers' stresses is considered, it is frequently accepted as a necessary component of teaching (Sachdeva and Kaur, 2013).

Influence of Teachers' Occupational Stress

Teachers have higher than average levels of stress and psychosomatic problems compared to those in other occupations. Stress among teachers has a big influence on the education, students' motivation and their health. Organizations are pushing employees to the limit in this contemporary, fiercely competitive environment to get the most out of them in the quest for greater profitability and sustainability. Additionally, employees are working hard to qualify for substantial bonuses and wages. The human body is bearing the brunt of excessive effort and exertion in this process of achieving maximum production and rewards because there are professions that include human

interaction and demand quick decision-making abilities. In addition, the professions where these choices have a significant influence are the most stressful (Alarcon, Eschleman and Bowling, 2009). Teachers undoubtedly rank among the occupations with the highest levels of stress at work. Some of the factors that have been highlighted in numerous countries as contributing to an increase in stress-related disorders include the increasing burden on teachers, role overload and larger class sizes for each teacher and an increase in the number of students behaving in an inappropriate manner (Dunham and Varma, 1998). The teaching profession is a field that seems to be significantly affected by Teachers' stress, with teachers being exposed to conditions resulting in highly intense stress and pressure. In many contexts, teacher stress has been defined within the literature as a negative affective experience that is related to one's ability to cope with job-related stressors (Kyriacou, 2001).

Review of related literature

Rekha Singh, Baig Muntajeb Ali, Shraddha Walekar Ghaisas, Boddireddy Sridevi and Divya Priya (2022) conducted a study on the Attitude of Teachers, Students and Parents towards continuous and comprehensive evaluation. The study employs the survey approach. A sample of 50 teachers, 50 students, and 50 parents was chosen using a simple random sampling technique. The data is collected using a self-made tool. The data is analyzed using the mean, standard deviation, and t-test. The research is limited to only 5 C.B.S.E. schools in the Bulandshahr District. The data was collected using a survey method from ten schools with CBSE instructors, students, and parents as a sample. To achieve the study's goal, a random purposive sample technique is used. The data is collected using a self-made tool called the "Comprehensive and Continuous Evaluation Attitude Scale (CCEAS)." It has 32 items and uses statistical techniques like Mean, SD, and t-test (critical ratio). That there is no significant difference between parents and students' attitudes towards CCE at the high school level in C.B.S.E. is accepted. There is no significant difference between teachers and students' attitudes towards CCE at the high school level in C.B.S.E. is accepted. Parents' attitudes towards the C.C.E. system at the high school level in C.B.S.E. were moderate. 2. Teachers' attitudes regarding the C.C.E. system at the high school level in C.B.S.E. were moderate. 3. Students in C.B.S.E. high schools had a moderate attitude towards the C.C.E. system. 4. There was no substantial variation in attitudes regarding the C.C.E. system between parents and teachers. 5. There was no discernible change in teacher and student attitudes regarding C.C.E.

Meenu Aggarwal and Sunita (2020) conducted a study on Compare the Attitude of Secondary School Teachers Towards Continuous and Comprehensive Evaluation (CCE) in relation to Gender and Types of School. One hundred secondary school teachers were selected by random sampling from five schools, which were located in Delhi region. All subjects were healthy and normal. Vishal Sood and Arti Anand Attitude scale was used to assess the attitude of secondary

school teachers towards Continuous and Comprehensive Evaluation that was analyzed by using mean, S.D and t-test. The results showed that there is a significant difference in attitude of government and non-government secondary school teachers towards Continuous and Comprehensive Evaluation in child related and process related dimensions.

Amita Gupta and Aanchal Jain (2016) a comparative study of attitude of primary and secondary school teachers of Rampur district towards continuous and comprehensive evaluation. Random sampling technique was used to select 121 primary and secondary school teachers. 'Teacher's Attitude Scale Towards Continuous and Comprehensive Evaluation', developed by Vishal Sood and Arti Anand has been used for data collection. The results revealed that gender and level of teaching, no significant difference is found among teachers' attitude towards CCE. Also, in reference to teaching experience, no significant difference seems to exist in the attitude of primary and secondary school male teachers, but in case of female teachers, there is a significant difference among them in their attitude towards Continuous and Comprehensive Evaluation.

Bishnu Pada Roy (2019) A study on Continuous and Comprehensive Evaluation System Practiced in the Primary Schools with Reference to Kokrajhar District of Assam. In the present investigation the total population and sample is taken from the entire Kokrajhar district, which is subdivided into 5 (five) Educational Blocks. The total population for the Lower Primary School is 1078 and for the upper primary school are 131. So, the sample is selected considering the existing number of Schools. In the present investigation the investigator used stratified random sampling. Because, as per the nature of the area of investigation this stratified random sampling is appropriate. All teachers reported that they had proper time to conduct CCE during the specific year plan and the syllabus is suitable for CCE implementation. All teachers revealed that there were clubs in their schools and they were functional. Co-curricular activities were also conducted by all schools. Some schools were facing problems with CCE due to the shortage of teachers in the school. Most of the teachers handled classes with more than forty students and this made it difficult for them to give personal attention to students during assessment. Every child differs from the other with respect to his abilities and talent in each task. Teachers were not clear on how to make assessment in such situations.

Sen and Chakraborty (2017) revealed evaluation is a very important part of school education. The introduction of Continuous and CCE is considered as one of the major steps taken in this regard to improve and strengthen the quality of school education. CCE is not successfully implemented without the change of teachers' attitude regarding the evaluation system. The true implementation of this evaluation system depends upon the active participation of the teachers. The performance of the teachers greatly depends upon their attitude. In this paper an attempt has been

made to understand the awareness level of the in-service school teachers of secondary level. An attitude towards Comprehensive and Continued evaluation scales constructed by Vishal Sood and Arti Anand were administered to the sample. The total numbers of statements in the questionnaire were 48. General category secondary school teachers are a little bit more aware of the Continuous and Comprehensive Evaluation concern. Literature review did not support such findings but, in this study the investigator has found this result. Urban domain secondary school teachers are more aware about the Continuous and Comprehensive Evaluation concept. Perhaps they have space to interact with their counterparts and they exchange opinions to enrich themselves. Co-educational secondary school teachers have a favourable attitude towards continuous and comprehensive evaluation. Multidimensional environment helps them to outfit with the latest pace in the field of education.

Vaishalee Bhrigu, Shweta Dubey and Jyoti Singh (2021) conducted a study of occupational stress among school teachers of Rudrapur city, Uttarakhand. Three government, semi government and private schools were selected to draw the sample randomly. Approximately 10 school teachers were selected from every school using stratified random sampling, this makes a total of 90 school teachers. Data was collected through the Teacher Stress Scale by Tinku De. Frequency, percentage, mean, standard deviation and t-test were done using SPSS version 20.0. The findings revealed that the highest number of male teachers is in average stress level whereas maximum female teachers were under above average level of stress. In comparison to government school teachers; semi government and private school teachers were under more stress. Thus, it can be concluded that male and female teachers working in government, semi government and private schools lie under almost the similar level of stress. To help teachers to manage stress, authorities and policy makers should facilitate supportive and collaborative culture; should provide training for stress and time management, specific training to manage the behaviour of disruptive people; should provide leisure facilities to the faculty and should encourage involvement of faculty in decision-making.

Jojo Kurian and Roshna Varghese (2020) carried out a study on the Impact of Occupational Stress on the Performance of School Teachers in the State of Kerala. Data were collected from a sample of 308 teachers working in various Government, Aided and Unaided schools, affiliated to the State Board or CBSE or ICSE. Teachers from Pre-Primary, Primary and Secondary Sections were included in the survey. Survey was conducted using questionnaires, seeking information on the socio educational background, job details, opinion on the current organization, self-assessment of their personality, work ethics, expectation on work life balance, compensation, job satisfaction, Student teacher relationship, teaching style etc. The study reveals that stress has an adverse role on the performance of teachers. Researchers believe that the study would help the authorities concerned, in understanding the working conditions, job expectations and preferences of

the teachers and the various factors that contribute to their occupational stress and the impact of stress on their performance.

Anuradha Shukla (2020) did a study to measure occupational stress among government and private school teachers. A sample of hundred secondary school teachers from the government and private schools has been taken. The relevant data has been collected using standardized Sharma.M and Kaur. M Teacher's occupational stress scale (TOSS-SMKS) English. It has been found that most of the teachers are suffering from occupational stress, anxiety and depression because of the occupational issues. The researcher found that female teachers comparatively suffer from lots of occupational stress. As, they have to play different sorts of roles both at schools and home. Thus, teachers are suffering from the worst psychological problems. Our "2019 Teacher Wellbeing Index revealed that 72 percent of education professional describe themselves as stressed." Stress is very harmful for anyone as it weakens the immune system and reduces physical stamina. Stress for a long time may increase risk of heart disease, fatigue and many more ailments. Teachers suffer from irritability, exhaustion, depression and anxiety.

Selvavinayagam and Kaviarasu (2019) Conducted a study on occupational stress among the teachers of the primary schools in Dharmapuri district. The scale used in the study has been developed by researchers. 370 Aided school teachers and 240 Government teachers have participated in the present study. At the end of the study it was seen that Aided school teachers have more occupational stress levels than Government school teachers. There is a meaningful difference in the stress level points of Government and Aided Primary Teachers. Policy makers are advised to analyse the teacher training and assessment system with the assumption that personal and social characteristics and working conditions may have an effect on teacher occupational stress. Results also showed that teachers who reported greater stress were less satisfied with teaching, reported greater frequency of absences and a greater number of total days absent, were more likely to leave teaching (career intention), and less likely to take up a teaching career again (career commitment).

Sekhar Babu (2019) carried out the research on effect of teachers' stress among primary school teachers. Randomly selected 200 teachers from primary schools in Kadapa district, Andhra Pradesh as a sample. Teachers stress attitude questionnaire was opted. The results revealed that no difference in teachers stress of secondary school teachers in terms of gender, management and locality.

Need and significance of the study

CCE is the development of comprehensively addressing knowledge, skills and dispositions. Different stakeholders, including instructors, are unsure about the required level of learning, the standards by which it might be assessed or how to keep their initiatives moving in the right direction. They cannot handle the issue of educational quality until they understand how educational institutions operate at the classroom, school, state, national and worldwide levels in terms of student learning and presentation. In order to enable them to track the learning improvement of children and provide timely assistance to close the learning gaps, suitable monitoring measures, i.e., criteria reflecting the holistic development of learners and assessment procedures, need to be in place and integrated with the educational system.

To address the quality issues, it is essential to conduct an assessment at both the macro and micro levels. Both have merits, but CCE can raise the ranking of education in macro-evaluations because it is a school-based system of assessment. This is due to the ability to chart learning progress against explicitly defined subject- and class-level learning goals and implement remedial actions at the local level. This will assist schools in ensuring that the curriculum requirements outlined in the National Curriculum Framework are met.

Statement of the problem

The present study aimed to address the research gaps identified in literature by examining the relationship between the attitude towards CCE and Occupational stress levels in primary schools. The findings of this study will provide valuable insights into the challenges and opportunities related with the improvement of attitude and Occupational Stress management skills. Thus the problem was stated as **“Predictors of Occupational Stress, Attitude towards CCE of Primary School teachers”**

Research methodology

In this study, the researcher used a descriptive survey method. The population consists of 5385 government primary school teachers in Warangal district of Telangana. A sample of 800 government primary school teachers was selected using a stratified random sampling technique.

Tools

The researcher used the following tools for the research

- Teacher’s Attitude Scale towards CCE by **Vishal Sood and Aarti Anand.(2011)**
- Teachers’ Occupational Stress Scale by **Mariya Aftab and Tahira Khatoon.(2014)**

Teachers Occupational Stress Scale and Teachers Attitude Scale Towards CCE these two adopted and used after establishing the reliability and validity through different suitable method

Key words

Attitude towards CCE

Attitude towards CCE refers to a set of emotions, beliefs and behaviors of primary school teachers towards the implementation of CCE and its components, which are often the result of experience, have a powerful influence on behavior and work efficiency.

Teachers' Occupational Stress

Teachers' Occupational stress has been operationally defined as the experience of negative emotions such as frustration, worry, anxiety and depression of primary school teachers in implementation of CCE.

Primary schools: The schools which offer classes from 1st to 5th are considered primary schools in the present study.

Objectives

- To predict the Occupational Stress and Attitude towards CCE Attitudes towards CCE of primary school teachers with the help of all independent variables. (Gender, Locality, Experience, Age, Academic Qualification and Professional Qualification.)

Hypotheses

- No single variable or a set of variables (all independent variables (6)) included in the study do not significantly exert their contribution to attitude towards CCE.
- No single variable or a set of variables (all independent variables (6)) included in the study do not significantly exert their contribution to Teachers' stress.

Data analysis

Multiple regression analysis: It is useful for determining what variables are affecting different variables of research and to describe and understand the relationship among variables. To predict new observations, to adjust and control the process the results of multiple regression will support.

Multiple regression

Step-wise Multiple Regression Analysis of Attitude of primary school teachers towards CCE with reference to demographic variables

This section deals with the analysis of the relative contribution or magnitude of the effect of each of the different independent variables on the dependent variable. The Attitude of primary school teachers towards CCE is predicted with the help of independent variables.

Attitude of primary school teachers towards CCE (AOCCE) (i.e.) variable number 7 in the Table is the dependent variable in the present investigation. Attitude of primary school teachers towards CCE is very important and is related to a number of demographic variables.

The step – wise multiple regressions are employed in the present investigation to predict the dependent variable with the help of independent variables. There are 7 variables in the present study. Attitude of primary school teachers towards CCE is as the dependent variable and 6 variables are as independent variables. The variable number, description of the variable and symbol used are presented in below table 1.

Table 1 Variables used for Regression Analysis

Variable Number (VN)	Description of the variable	Symbol used
1	Locality	L
2	Gender	G
3	Experience	E
4	Professional qualification	PQ
5	Academic qualification	AQ
6	Age	A
7	Attitude of primary school teachers towards CCE	AOCCE
8	Teachers’ Occupational Stress	TOS

The prediction of Attitude of primary school teachers towards CCE scores (AOCCE) and the relative contribution of various variables on the dependent variable (AOCCE) is studied, with the help of step-wise multiple regression analysis. The prediction of Occupational Stress Levels of primary school teachers (TOS) and the relative contribution of various variables on the dependent variable (TOS) is studied, with the help of step-wise multiple regression analysis. Step-wise Multiple Regression Analysis of Attitude towards CCE with reference to Socio-demographic variables

Hypothesis

No single variable or a set of variables (all independent variables (6)) included in the study do not significantly exert their contribution to attitude towards CCE.

The results of the regression analysis are reported in Table 2

Table 2 Prediction of Attitude towards CCE with the help of all independent variables (1-6)

Step No.	IV (VN)	R	R ²	SE R	F value for R	b (VN)	't' value for b	Constant	B	R	percent Variance
1	A (6)	0.086	0.007	9.329	5.918* (1, 798)	-0.941 (6)	2.43*	143.298	-0.086	-0.086	0.736

It is seen from the Table that the first variable entered into the step - wise regression analysis is Age (A). The multiple correlation (R) obtained is 0.086. It implies that the strength of the relationship between the two variables (Attitude towards CCE and A) is about 8.60 percent. It could be seen that R is significant (F = 5.918) beyond 0.01 level of significance for 1 and 798 degrees of freedom. The critical value of 'F' is 3.85 at 0.05 level and 6.66 at 0.01 levels for 1 and 798 degrees of freedom. The coefficient of multiple R² is 0.007.

This shows that 0.70 percent of the variance in Attitude towards CCE is accounted for by A. The standard error of Multiple R (SER) is 9.329. From this it may be inferred that nearly 68 percent of actual Attitude towards CCE value would lie within $M \pm 9.329$ of Attitude towards CCE value predicted with the help of this variable (A). The partial regression coefficient (b) presented in the column '7' is -0.941. This value indicates that Attitude towards CCE value would change by -0.941 units for every one unit of change in A. The 't' value for b is 2.43 which is significant at 0.05 level. The value of the constant that could be written to predict Attitude towards CCE at this stage is 143.298. The general formed of multiple regression equation may be written as

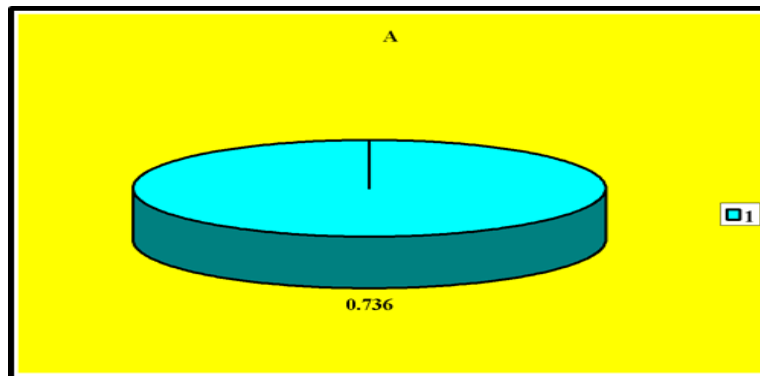
$$Y = A + b_1 (X_1) + b_2 (X_2) + b_3 (X_3) + \dots + b_n (X_n)$$

Where Y is predicted score on the dependent variable; b₁, b₂, b₃ ... b_n are partial regression coefficients; X₁, X₂, X₃.....X_n are scores on different independent variables and A is constant. Thus, the multiple regression equation at the end of this step, could be written as

$$\text{Attitude towards CCE} = 143.298 + (-0.941) (A)$$

It is observed from Table 1 that it could be possible to explain 0.736 percent of variance in the dependent variable Attitude towards CCE, with the help of Age. Thus, it is concluded that Attitude towards CCE score could best be predicted with the help of age among the six (1-6) independent variables. Hence, the hypothesis was rejected. The pie diagram showing the percentage of variance of all independent variables to predict Attitude towards CCE is shown in Figure1.

Figure 1 Pie diagram showing the percentage of variance of all independent variables to predict Attitude towards CCE



Step-wise Multiple Regression Analysis of Teachers’ Occupational stress with reference to Socio-demographic variables. This section deals with the analysis of the relative contribution or magnitude of the effect of each of the different independent variables to the dependent variable. The Teachers’ Occupational stress is predicted with the help of independent variables.

Hypothesis

No single variable or a set of variables (all independent variables (6)) included in the study do not significantly exert their contribution to Teachers’ stress.

The results of the regression analysis are reported in Table 3.

Table 3 Prediction of Teachers’ stress with the help of all independent variables (1-6)

Step No.	IV (VN)	R	R ²	SE R	F value for R	b (VN)	‘t’ value for b	Constant	B	R	percent Variance
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1.	PQ (4)	0.09 5	0.00 9	9.053	7.325* * (1, 798)	- 1.872 (4)	2.71**	56.883	- 0.09 5	- 0.09 5	0.910
2.	G (2)	0.12 2	0.01 5	9.032	6.008* * (2, 797)	- 1.944 (4) - 1.380 (2)	2.81** 2.16*	59.085	- 0.09 9 - 0.07 6	- 0.07 1	0.945 0.540
3.	A (6)	0.14 2	0.02 0	9.014	5.424* * (3, 796)	- 1.776 (4) - 1.313 (2) - 0.773 (6)	2.56* 2.05* 2.05*	60.587	- 0.09 1 - 0.07 2 - 0.07 3	- 0.08 6	0.863 0.514 0.626
4.	L (1)	0.15 7	0.02 5	8.999	4.996* * (4, 795)	- 1.914 (4) - 1.317 (2) - 0.799 (6) 1.225 (1)	2.75** 2.06* 2.12* 1.91 [@]	59.071	- 0.09 8 - 0.07 3 - 0.07 5 0.06 7	0.05 3	0.930 0.516 0.647 0.359

It is seen from the Table that the first variable entered into the step-wise regression analysis is Professional Qualification (PQ). The multiple correlation (R) obtained is 0.095. It implies that the

strength of the relationship between the two variables (Teachers' Stress and PQ) is about 9.50 percent. It could be seen that R is significant ($F = 7.325$) beyond 0.01 level of significance for 1 and 798 degrees of freedom. The critical value of 'F' is 3.85 at 0.05 level and 6.66 at 0.01 levels for 1 and 798 degrees of freedom. The coefficient of multiple R^2 is 0.009. This shows that 0.90 percent of the variance in Teachers' Stress is accounted for by PQ.

The standard error of Multiple R (SER) is 9.053. From this it may be inferred that nearly 68 percent of actual Teachers' Stress value would lie within $M \pm 9.053$ of Teachers' Stress value predicted with the help of this variable (PQ). The partial regression coefficient (b) presented in the column '7' is -1.872. This value indicates that Teachers' Stress value would change by -1.872 units for every one unit of change in PQ. The 't' value for b is 2.71 which is highly significant at 0.01 level. The value of the constant that could be written to predict OS at this stage is 56.883.

The general formed of multiple regression equation may be written as

$$Y = A + b_1 (X_1) + b_2 (X_2) + b_3 (X_3) + \dots + b_n (X_n)$$

Where Y is predicted score on the dependent variable; $b_1, b_2, b_3 \dots$ banere partial regression coefficients; $X_1, X_2, X_3, \dots, X_n$ are scores on different independent variables and A is constant. Thus the multiple regression equation at the end of this step, could be written as

$$\text{Teachers' Stress} = 56.883 + (-1.872) (PQ)$$

Gender (G) is entered into the step - wise regression analysis as the second most significant variable. The multiple correlations (R) between Teachers' Stress on one side and PQ and G on the other side are 0.122. Thus, the strength of the relationship between Teachers' Stress and the two independent variables put together is 12.20 percent. R is significant at 0.01 level ($F = 6.008$, degrees of freedom 2, 797). The value of R^2 is 0.0149. This shows that the two variables put together could explain 1.49 percent of variance in the dependent variable (Teachers' Stress). Out of this 0.945 percent of variance is explained by PQ. The remaining 0.540 percent of variance is accounted for by G (Table 49, Col. 12). The regression equation to predict OS with these two variables (PQ and G) as predictor variables is: $\text{Teachers' Stress} = 59.085 + (-1.944) (PQ) + (-1.380) (G)$

Where 29.085 is the constant to be considered at this step and -1.944 and

-1.380 is the partial regression coefficients of Professional qualification and Gender. The 'b' values for the variables are significant at 0.01 level.

There would not be much increase in R^2 after the 3rd step.

The regression equation at the end of 3rd step could be written as

$$\text{Teachers' Stress} = 60.587 + (-1.776) (\text{PQ}) + (-1.313) (\text{G}) + (-0.773) (\text{A})$$

It is observed from Table 50 that it could be possible to explain 2.00 percent of variance in the dependent variable TS, with the help of above three variables.

There are four steps in this regression analysis.

The regression equation at the end of 4th step could be written as;

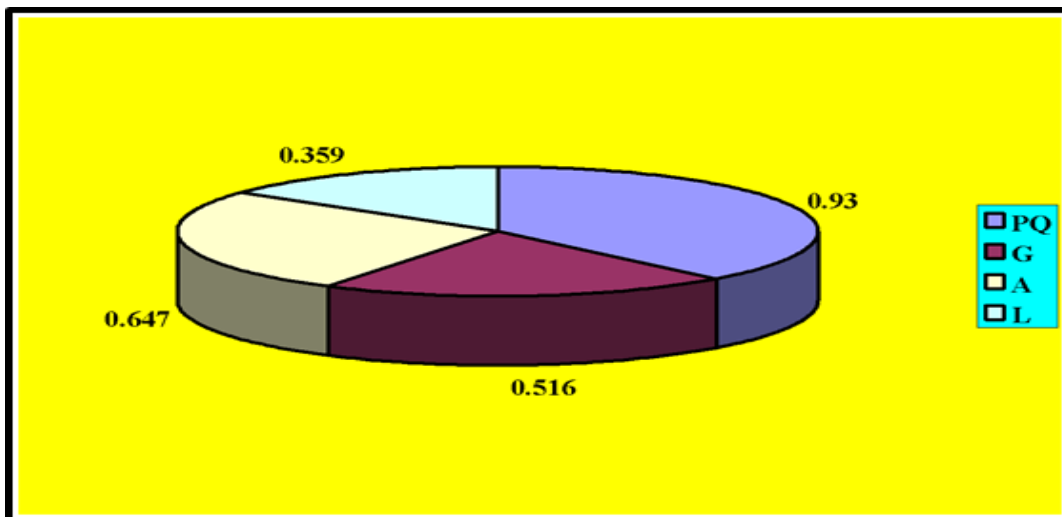
$$\text{Teachers' Stress} = 59.071 + (-1.914) (\text{PQ}) + (-1.317) (\text{G}) + (-0.799) (\text{A}) + (1.225) (\text{L})$$

It is observed from the Table that it could be possible to explain 2.45 percent of variance in the dependent variable OS, with the above Four variables.

Hence it is concluded that Teachers' stress score could best be predicted with the help of Professional qualification, Gender, Age and Locality among the Six (1-6) independent variables. Hence, the hypothesis was rejected.

The pie diagram showing the percentage of variance of all independent variables to predict Teachers' stress is shown in Figure 2.

Figure 2 Pie diagram showing the percentage of variance of all independent variables to predict Teachers' stress



Findings of the study

Thus, it is concluded that Attitude towards CCE score could best be predicted with the help of age among the six (1-6) independent variables.

Hence it is concluded that Teachers' stress score could best be predicted with the help of Professional qualification, Gender, Age and Locality among the Six (1-6) independent variables.

Discussion

Most of the teachers have a moderate level of Attitude means they are with a positive attitude towards CCE.

Here, the attitude is influenced by many variables, age is showing more influence than other predictors like locality, gender, experience, professional Qualification and Academic qualification. Younger Primary school teachers showed more favourable attitudes than older teachers.

Occupational stress of primary school teachers is influenced by their age, gender, Locality and professional qualification. Urban teachers have more stress than rural teachers, female teachers have more stress than male, younger teachers have less stress than older, professionally highly qualified teachers have higher stress levels than others.

Educational implications

- Orientation programs should focus on specific objectives to increase awareness of CCE among teachers for effective implementation in schools and to build a positive attitude towards CCE workshops should provide opportunities for teachers to address doubts and difficulties and share innovative ideas. Training programs on CCE are essential for teachers and should be provided by resource persons with expertise in CCE.
- Orientation programs should focus on specific objectives to increase awareness of CCE among teachers for effective implementation in schools. CCE workshops should provide opportunities for teachers to address doubts and difficulties and share innovative ideas. Training programs on CCE are essential for teachers and should be provided by resource persons with expertise in CCE.
- This research study will be useful for decision makers, teachers, principals, policy makers and education planners in designing policies and making structural changes in syllabus and teaching methods. It will serve as a solid base for the implementation of CCE by providing information on the opinions, perceptions and awareness of respondents. The results can help make the implementation of CCE in schools more efficient and transparent. This research can also work as a comprehensive and updated review for further studies on the implementation of CCE and be useful for other researchers in the same area. The management committee of the school should organize remedial instructional programs after diagnosing problems faced by teachers in the classroom. Regular monitoring and administration should be carried out by higher authorities, with face-to-face sessions conducted with teachers to solve their queries and offer necessary support for the proper execution of CCE.

- Parents play a crucial role in the success of any education system. While some parents are satisfied with their child's progress and holistic development, others may not be clear on the concept of Continuous and Comprehensive Evaluation. To make this scheme more successful, it is important to intensify the orientation of parents at both school and block levels. Parents should pay attention to their child's performance and take an interest in assigned tasks such as projects. Their constant engagement and support can motivate children to reach their full potential.

Conclusion

The CCE model has the potential to significantly transform India's education system into one that is more learner-centric. To address operational and implementation challenges, it is important to provide adequate teaching resources and training facilities. The new teaching-learning patterns introduced by CCE will ultimately lead to a stress-free education in India. To achieve this, Indian schools must have reasonable teacher-student ratios and foster a more equal, collaborative relationship between teachers and students in the pursuit of knowledge construction.

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AI-Enhanced Handlooms: Scaling Handmade Textile Production for Sustainability, Economic Equity, and Climate Resilience

Abstract

Handmade textiles have long been central to India's cultural and economic identity, offering sustainable alternatives to industrially produced fabrics. However, in an era of climate urgency, their limited scalability and the lack of awareness of their potential to mitigate climate change present a challenge. While handmade fabric production is inherently sustainable—relying on natural fibers, minimal energy consumption, and eco-friendly techniques—the sector struggles with quality inconsistencies, high labor costs, and inefficiencies that limit its ability to compete in global markets. This paper examines how artificial intelligence (AI) can optimize handmade textile production without disrupting the authenticity of craftsmanship. Drawing from pre-British-era artisan manufacturing models, it highlights how historically decentralized yet organized structures enabled scalable, high-quality textile production. Unlike today's fragmented supply chains, these earlier systems thrived on collaborative production, skill-based specialization, and local trade networks, ensuring artisans focused on manufacturing while merchants handled distribution. The paper argues that reintroducing these traditional models, enhanced with AI-driven quality assessment, defect detection, and precision weaving, can improve efficiency and scale while retaining artisan agency. Beyond environmental sustainability, the expansion of handmade textiles holds significant economic and social benefits. Scaling this sector can reduce inequality by creating decentralized employment and strengthen the cultural economy by preserving traditional skills. Furthermore, handmade fabrics, crafted with natural dyes and organic materials, contribute to human health and well-being. The paper presents a policy framework for AI integration in handmade textile production, ensuring scalability while maintaining ecological, economic, and cultural integrity. By leveraging technology without over-automation, India's artisan economy can become a cornerstone of sustainable fashion and climate-conscious textile production.

1. Introduction

1.1 Overview of Handmade Textiles in India: Cultural Significance and Economic Role

India's handmade textile industry is one of the oldest in the world, with evidence of its existence dating back to the Indus Valley Civilization (circa 2500 BCE) (Indian Culture Portal, 2024). The country has a rich legacy of handwoven fabrics that are deeply intertwined with its cultural identity and rural economy. Historically, Indian textiles were highly sought after in global trade, with fabrics such as calico, muslin, and khadi being exported to Europe, Africa, and Southeast Asia (Vision IAS, 2024). Handmade textiles are produced using traditional techniques that vary across regions, each employing distinct weaving, dyeing, and printing methods. India's fabric traditions include **khadi**, a hand-spun, handwoven fabric that became a symbol of the independence movement and remains an icon of sustainability today; **calico**, a plain-woven cotton fabric originally from Calicut, known for its durability; **muslin**, a finely woven cotton fabric from Bengal, famous for its lightweight texture; **ikat**, a resist-dyed fabric from Odisha, Telangana, and Gujarat, featuring blurred patterns created through pre-dyed yarns; **jamdani**, a West Bengal handwoven cotton textile with elaborate floral motifs; **Kota Doria**, a lightweight, airy fabric from Rajasthan with a square-check pattern; and traditional block-printed fabrics like **Ajrak** and **Bagru** from Gujarat and Rajasthan, known for their use of natural dyes (Indian Culture Portal, 2024).

The Indian textile industry remains one of the largest employment generators, with over 45 million people directly employed and an additional 55 million indirectly engaged in associated activities (Indian Textile Journal, 2024). The sector contributes approximately 2.3% of India's GDP, 12% of export earnings, and 13% of industrial production (Vision IAS, 2024). Despite these impressive numbers, the handloom sector struggles to compete with mechanized textile production, necessitating innovative solutions for scalability.

1.2 The Sustainability Benefits of Handmade Textiles

Unlike industrial textile production, handmade textiles offer multiple sustainability advantages:

- **Eco-friendly raw materials:** Most handmade fabrics utilize natural fibers like cotton, silk, wool, and linen, reducing environmental impact.
- **Minimal energy consumption:** Since weaving and dyeing are often done manually, handmade textile production has a significantly lower carbon footprint compared to mechanized processes.
- **Reduced water and chemical usage:** Many traditional dyeing techniques employ natural dyes (vegetable-based or azo-free), preventing toxic industrial runoff.

- **Less textile waste:** The handmade textile sector produces less waste due to its small-batch, made-to-order model. Fabric scraps are frequently repurposed into quilts, patchwork garments, or accessories, minimizing landfill contributions (Indian Textile Journal, 2024).

While these factors make handmade textiles inherently sustainable, their limited scalability and cost inefficiencies pose challenges in today's competitive market.

1.3 Challenges in Scalability and Market Competitiveness

Despite their sustainability and heritage value, handmade textiles face several obstacles:

- **Quality inconsistencies:** Handwoven fabrics often show slight irregularities, making it difficult to standardize quality for mass production. The awareness of the same has increased to understand that these are handmade made and uniformity is usually a challenge.
- **High labor costs:** Unlike mechanized mills, the process of hand-spinning, weaving, and dyeing is labor-intensive, increasing the cost of production.
- **Market fragmentation:** Most artisans operate within disjointed supply chains, lacking access to global markets and streamlined distribution networks.
- **Lack of technological integration:** While industrial textile production has rapidly adopted AI and automation, the handmade textile sector has been slow to embrace modern tools that could enhance efficiency.

1.4 The Role of AI in Enhancing, Rather Than Replacing, Artisan Craftsmanship

Artificial Intelligence (AI) presents an opportunity to enhance, rather than replace, handmade textile production. AI-driven tools can:

- **Improve quality control** by detecting weaving defects early, reducing material wastage.
- **Enhance precision weaving** by assisting artisans with guided weaving technologies.
- **Optimize supply chain efficiency** by predicting demand, reducing inventory costs, and enabling direct-to-consumer (D2C) models through AI-powered e-commerce.
- **Support design innovation** by using AI to analyze historical patterns and generate contemporary adaptations, keeping traditional crafts relevant (Vision IAS, 2024).

By leveraging AI strategically, handmade textiles can achieve greater scalability while retaining the authenticity of craftsmanship and ensuring artisan agency.

1.5 Objectives of the Paper

This paper aims to:

1. Highlight the need for scaling handmade textiles to promote sustainability, economic equity, and climate resilience.
2. Analyze historical artisan production models that enabled scalability before industrialization disrupted traditional supply chains.
3. Examine the challenges faced by the sector today and how AI can address these issues.
4. Propose a framework for AI integration that enhances production efficiency while preserving craftsmanship.
5. Offer policy recommendations to create an enabling environment for AI-assisted handloom production without over-automation.

By exploring the intersection of heritage craftsmanship, AI technology, and sustainable economic development, this paper advocates for a future where handmade textiles remain competitive in the modern world.

2. Literature Review

1. The Need for Scaling Handmade Textiles

Handmade textiles represent a crucial yet underutilized solution in the pursuit of **sustainability, economic equity, and climate resilience**. While industrial textile production has grown exponentially, its environmental and social consequences necessitate a shift toward more sustainable and inclusive production models. Scaling handmade textile production provides an opportunity to mitigate climate impact, empower artisan communities, and build a more resilient fashion economy.

1.1. Sustainability: Reducing the Environmental Impact of Textile Production

The global fashion industry is responsible for approximately **10% of global carbon emissions** and **20% of wastewater pollution** (Ellen MacArthur Foundation, 2024). Industrial textile production consumes vast amounts of energy, water, and chemicals, contributing to deforestation, soil degradation, and pollution. In contrast, handmade textile production offers several environmental benefits:

- **Low Carbon Footprint:** Unlike mechanized textile mills, handmade fabrics rely on manual processes such as hand-spinning, weaving, and natural dyeing, drastically reducing energy consumption.
- **Water Conservation:** Many traditional techniques, such as block printing and vegetable dyeing, use significantly less water than chemical-based industrial dyeing processes.

- **Less Textile Waste:** Industrial fashion production leads to massive overproduction and landfill waste. Handmade textiles, produced in small batches and often repurposed, align with circular economy principles.

By scaling handmade textile production, fashion brands can **reduce their environmental footprint** while offering consumers an ethically produced alternative.

1.2. Economic Equity: Empowering Artisans and Strengthening Local Economies

Handloom and handmade textile industries are one of the largest sources of rural employment in India, with over **4.33 million artisans** directly dependent on handloom weaving (Ministry of Textiles, 2024). However, these artisans often face low wages, poor market access, and declining demand due to mass-produced, low-cost alternatives. Scaling handmade textile production can:

- **Increase Artisan Incomes:** Structured scalability allows for better wage distribution and more consistent employment for artisans.
- **Promote Gender Equity:** A significant percentage of artisans in the handmade textile sector are women, making expansion a tool for **women's economic empowerment**.
- **Revive Traditional Skills:** Generations-old weaving and dyeing techniques are at risk of disappearing. Scaling production ensures these skills are passed down and remain commercially viable.

By creating a more **organized production model** with fair trade policies and digital access, artisans can directly engage with domestic and global markets, reducing dependency on exploitative intermediaries.

1.3. Climate Resilience: Strengthening Supply Chain Adaptability

The climate crisis poses a major threat to textile production, especially in water-stressed regions reliant on industrial processes. Handmade textiles offer a more **climate-resilient** alternative:

- **Locally Sourced Materials:** Many handmade fabrics use indigenous, climate-adapted fibers such as khadi cotton, eri silk, and wool, reducing reliance on imported synthetic materials.
- **Decentralized Production:** Unlike centralized factories, handmade textile production is **geographically dispersed**, making it more resilient to climate-related disruptions like floods or supply chain breakdowns.
- **Biodegradable and Regenerative Practices:** Natural fibers and dyes reduce soil and water contamination, supporting sustainable agriculture and biodiversity conservation.

As climate instability threatens **industrial supply chains**, scaling handmade textiles provides an **adaptive and resilient production model** that aligns with sustainability goals.

1.4. The Need for a Structured Approach to Scalability

Despite its potential, the handmade textile sector faces **structural and systemic barriers** to large-scale production:

- **Lack of Technology Integration:** Many artisans rely on traditional methods without access to AI-driven quality control or predictive market analytics.
- **Fragmented Supply Chains:** Weak infrastructure and limited direct-to-market channels prevent seamless scalability.
- **Inconsistent Quality Standards:** Handmade products often face rejection in global markets due to minor imperfections. AI-enhanced precision tools can address this issue.
- **Limited Investment and Policy Support:** Government schemes exist but need better implementation and integration with **climate finance** initiatives.

A **structured roadmap for scaling** must integrate **AI tools for efficiency**, **market linkages for fair pricing**, and **policy interventions for artisan welfare**, ensuring handmade textiles thrive in a competitive, sustainability-driven global economy.

2. Historical Artisan Production Models and Their Scalability Before Industrialization

2.1 The Scale and Structure of Pre-Industrial Artisan Networks

Before industrialization disrupted traditional supply chains, India’s handmade textile production operated within an organized yet decentralized system. The artisan economy thrived on localized production, skilled labor specialization, and community-based trade networks. Unlike today’s fragmented supply chains, these historical models enabled scalability through structured collaboration and efficient resource utilization.

2.2 Comparison of Historical vs. Modern Handmade Textile Production

Factor	Pre-Industrial Artisan Model (Before 1800s)	Modern Handmade Textile Model (Post-Industrial Era)
Production Scale	High—regional clusters produced for domestic and global markets (e.g., Bengal muslin, Gujarat block prints)	Low—fragmented clusters with limited market access
Labor Structure	Specialized guilds with generational expertise; division of labor ensured high efficiency	Decentralized artisans with little coordination; lack of generational continuity

Market Reach	Strong global exports (Asia, Middle East, Europe); facilitated by structured merchant networks	Limited due to industrial competition and supply chain inefficiencies
Raw Material Sourcing	Locally sourced organic cotton, silk, and wool; sustainable production cycles	Mix of natural and synthetic fibers, often sourced from global supply chains
Quality Control	Standardized processes within guilds ensured high quality and durability	Inconsistent quality due to lack of centralized oversight and training
Economic Contribution	Estimated 25-30% of India’s GDP in the 17th-18th centuries (Roy, 2020)	Currently contributes ~2.3% to India’s GDP (Vision IAS, 2024)
Environmental Impact	Minimal—no synthetic dyes, low water usage, biodegradable waste	Significant—chemical dyeing, high water consumption, textile waste

2.3 Mechanisms That Enabled Scalability Before Industrialization

1. Guild-Based Manufacturing & Decentralized Production:

- a. Before British colonization, India’s textile industry was organized through artisanal guilds. These guilds-maintained quality control, trained apprentices, and ensured steady production volumes. Unlike today’s scattered artisan workforce, this structure enabled continuous production while maintaining high quality.
- b. The caste-based occupational structure played a role in maintaining expertise. The Julahas (Muslim weavers) in Bengal, the Devangas in Karnataka, and the Padmasalis in Andhra Pradesh specialized in distinct weaving traditions, ensuring continuity of skill transmission (Roy, 2020).

2. Merchants as Supply Chain Facilitators:

- a. Merchants played a crucial role in supply chain efficiency, handling logistics, financing, and trade negotiations. In contrast, modern artisans often struggle with direct market access, leading to dependency on middlemen with exploitative pricing structures.
- b. The Banjaras, a nomadic trading community, acted as transporters of raw materials and finished goods, ensuring seamless movement across regions (Habib, 2001).

3. Localized Raw Material Sourcing:

- a. Cotton, silk, and wool production were closely linked to weaving centers, reducing transportation inefficiencies. Today, raw materials are often outsourced globally, leading to increased costs and carbon footprints.
- b. In pre-industrial India, silk weaving communities such as the Khattris in Gujarat and the Tanti weavers in Bengal sourced their silk locally, maintaining sustainable production cycles (Das, 2018).

4. Integrated Regional Specialization:

- a. Distinct regions specialized in specific textiles (e.g., Kanchipuram silk in Tamil Nadu, Patola weaving in Gujarat), ensuring optimized skill development and efficiency. Today, these clusters remain, but the lack of structured market linkages has limited their scalability.
- b. The weavers of Varanasi's Banarasi silk, for example, operated within an ecosystem where dyers, spinners, and designers collaborated seamlessly to maintain high production volumes (Chakravarti, 2015).

2.4 Lessons for AI-Enhanced Scaling of Handmade Textiles

By drawing from these historical models, AI-driven systems can help:

- **Enhance quality control** through AI-based defect detection and weaving precision.
- **Revive localized production networks** by facilitating digital market access and decentralized production clusters.
- **Improve raw material tracking and sourcing** using AI-powered supply chain management.
- **Enable fair pricing and transparency** by reducing dependence on exploitative intermediaries.

Understanding the strengths of historical models provides a roadmap for AI-enhanced handmade textile production, balancing tradition with technological innovation to drive sustainable growth.

3. Examining the Challenges Faced by the Sector Today and How AI Can Address These Issues

3.1 Current Challenges in Handmade Textile Production

1. Fragmented Workforce & Loss of Traditional Knowledge

- a. The breakdown of historical artisan guilds has left artisans working in isolation, leading to skill erosion due to a lack of formal training and generational knowledge transfer (Amutha, 2021).
- b. Younger generations are reluctant to enter the sector due to limited financial security and growth opportunities (Sharma and Ranjan, 2023).

2. Market Access & Middlemen Dependency

- a. Artisans struggle to reach direct consumers, often relying on intermediaries who take a significant share of profits (Sharma and Ranjan, 2023).
- b. Limited digital literacy and access to e-commerce platforms further hinder market expansion.

3. Quality Control & Standardization Issues

- a. Unlike industrial textiles, handmade fabrics often face inconsistencies in weave, dyeing, and finishing, making it difficult to meet global market standards (Amutha, 2021).
- b. Lack of structured quality assurance mechanisms results in high rejection rates and financial losses.

4. Raw Material Sourcing & Sustainability

- a. Dependence on imported raw materials increases costs and carbon footprints.
- b. Traditional dyeing processes often release untreated waste into water bodies, impacting sustainability (BK Allied, 2024).

5. Financial Constraints & Limited Investment

- a. Artisans have limited access to institutional credit and investment opportunities (Sharma and Ranjan, 2023).
- b. Government subsidies and grants often fail to reach grassroots artisans due to bureaucratic inefficiencies.

3.2 AI-Driven Solutions for the Handmade Textile Sector

1. AI-Based Skill Preservation & Training

- a. Digital platforms with AI-powered tutorials and virtual apprenticeships can help artisans upskill and preserve traditional techniques (JETIR, 2021).
- b. AI-assisted design tools can support artisans in adapting traditional motifs to modern market trends.

2. Blockchain & AI for Transparent Market Access

- a. AI-driven e-commerce platforms can enable direct-to-consumer sales, reducing dependency on intermediaries.
- b. Blockchain technology can ensure fair pricing, traceability, and authenticity verification for handmade textiles (IJIRM, 2024).

3. AI-Powered Quality Control & Standardization

- a. AI-enabled defect detection using computer vision can help artisans maintain consistent quality standards (Springer, 2021).

- b. Automated grading systems can assess fabric texture, weave density, and color accuracy, reducing rejection rates.

4. Smart Supply Chain Management

- a. AI-driven predictive analytics can optimize raw material sourcing, reducing costs and environmental impact (IJIRM, 2024).
- b. Machine learning algorithms can analyze demand trends, helping artisans align production with market needs.

5. AI-Enhanced Financial Inclusion

- a. AI-driven credit assessment models can facilitate access to microloans and investment opportunities for artisans (JETIR, 2021).
- b. Smart contracts can ensure transparent and timely payments, improving financial security.

3.3 Lessons for AI-Enhanced Scaling of Handmade Textiles

By integrating AI-driven solutions, the handmade textile sector can:

- **Enhance quality control** through AI-based defect detection and automated grading- Although accepted by awareness of handmade textiles of the unevenness; AI can control and avoid the knots, the defects etc via prior programming
- **Revive decentralized production networks** by facilitating direct market access. A thorough study to network the cluster community can be worked upon. A fresh census of this sector can bring a new umbrella of first hand assessed contacts.
- **Optimize raw material sourcing** using AI-powered predictive analytics. This is as well possible with data put together collectively. The idea is to put all the vendors to a directory.
- **Enable fair pricing and transparency** through blockchain-backed transactions. Once the network is established there is no middlemen and skill development is provided for craftsmen to communicate for themselves and to take consensus on the pricing.

Leveraging AI while respecting traditional craftsmanship can help scale handmade textile production sustainably, ensuring both economic viability and cultural preservation.

4. A Framework for AI Integration in Handmade Textile Production

4.1 Principles of AI Integration

To effectively integrate AI into handmade textile production while preserving craftsmanship, the following principles must be upheld:

- **Preservation of Artisan Knowledge:** AI must serve as an enabler rather than a replacement for traditional techniques. This can be achieved by incorporating AI as an assistant that enhances efficiency while ensuring that core handcrafting techniques remain intact (Chakrabarti and Sen, 2022).
- **Equitable Access to AI Tools:** Given the digital divide, AI solutions should be designed for ease of use by artisans with minimal technological literacy. This includes voice-enabled interfaces, mobile-based applications, and localized language support (Ghosh, 2023).
- **Sustainability & Circular Economy:** AI should facilitate resource optimization, waste reduction, and adherence to circular economy principles by predicting raw material needs and minimizing excess production (Jain et al., 2024).
- **Community-Driven Implementation:** AI adoption should be a participatory process, ensuring that artisans are actively involved in co-developing solutions that align with their needs and traditions (Patel, 2021).

4.2 AI Integration Model

1. AI-Enabled Design & Training

- a. AI-powered design software can enable artisans to digitally replicate traditional motifs while allowing for iterative design improvements based on contemporary fashion trends. This integration ensures that traditional aesthetics are retained while meeting modern consumer preferences (Mukherjee et al., 2023).
- b. AI-driven adaptive learning platforms can provide skill development modules tailored to artisans' experience levels, incorporating virtual reality (VR) for immersive weaving training (Desai and Kumar, 2022).

2. Smart Production Monitoring

- a. AI-integrated Internet of Things (IoT) systems can provide real-time monitoring of loom operations. Sensors can detect inconsistencies in weaving patterns and suggest corrective measures to artisans before defects occur, reducing wastage and enhancing precision (Ramesh and Bhat, 2023).
- b. AI can analyze production efficiency data, offering customized recommendations to artisans on optimizing tension, yarn selection, and weaving speed while ensuring that the handmade essence is preserved (Verma et al., 2024).

3. AI-Augmented Quality Assurance

- a. Machine learning algorithms trained on high-quality handmade textiles can assess fabric texture, weave density, and dye uniformity, assisting artisans in maintaining market standards. Such AI-powered assessments can significantly reduce rejection rates (Sharma and Nair, 2023).
- b. Predictive maintenance using AI can preemptively identify mechanical issues in traditional weaving setups, ensuring minimal disruptions and prolonging equipment lifespan (Sinha and Gupta, 2022).

4. Blockchain & AI for Ethical Supply Chains

- a. AI-integrated blockchain solutions can enhance supply chain transparency by tracking textiles from raw material procurement to final sale, ensuring ethical sourcing and fair-trade compliance (Krishnan, 2024).
- b. AI-enabled smart contracts can eliminate middlemen exploitation by automating wage disbursements, verifying artisan contributions, and ensuring timely payments, thereby enhancing economic security (Das and Rao, 2023).

5. Sustainable Resource Optimization

- a. AI-driven demand forecasting models can enable artisans to align production with market needs, reducing surplus production and associated environmental waste (Subramanian et al., 2024).
- b. Sustainable raw material selection can be enhanced through AI-based recommendations, which analyze cost, environmental impact, and availability to propose eco-friendly alternatives (Mehta, 2023).

4.3 Expected Impact of AI Integration

By strategically integrating AI into the handmade textile industry, the sector can witness transformative benefits:

- **Economic Empowerment:** Direct market access improved financial inclusion, and reduced exploitation by middlemen will lead to higher artisan earnings and greater financial stability (Sharma, 2024).
- **Enhanced Productivity:** AI-assisted production monitoring can help artisans optimize workflows while ensuring the artistic integrity of handmade textiles is not compromised (Ghosh, 2023).

- **Quality & Market Expansion:** AI-enabled quality assurance will allow handmade textiles to meet global industry standards, increasing their competitiveness in international markets (Mukherjee et al., 2023).
- **Sustainability:** AI-driven resource optimization will contribute to a greener, more sustainable production model, reducing carbon footprints and improving environmental outcomes (Jain et al., 2024).

By adopting a well-structured AI framework, the handmade textile sector can scale efficiently while maintaining its cultural and artisanal heritage, fostering a sustainable and equitable future.

5. Research Analysis-

5.1 AI Applications in Handmade Textile Production

The intersection of artificial intelligence (AI) and handmade textiles is an emerging field, with research exploring how technology can optimize craftsmanship without compromising authenticity. AI-driven solutions in the textile sector broadly fall into the following categories:

- **Quality Control and Defect Detection:** AI-powered image recognition and computer vision systems are being employed to identify defects in handwoven fabrics, ensuring consistency in production (Patel et al., 2023). Machine learning models trained on textile data can detect weaving inconsistencies, enabling artisans to make real-time corrections and reduce fabric wastage.
- **Design Assistance and Pattern Generation:** AI algorithms, particularly Generative Adversarial Networks (GANs), can analyze traditional textile patterns and generate contemporary adaptations, preserving heritage aesthetics while allowing for modern design innovation (Li & Wang, 2022).
- **Supply Chain Optimization:** AI-powered demand forecasting models enable better inventory management, reducing overproduction and ensuring artisans can work on demand-driven production cycles (Mishra et al., 2024). These models also facilitate dynamic pricing strategies for handmade textiles, improving profitability for artisans.
- **AI-Assisted Weaving:** While handloom weaving remains a manual process, AI-integrated smart looms and haptic guidance systems are being explored to enhance precision and efficiency without replacing human craftsmanship (Rao & Gupta, 2024). Such tools can assist artisans in complex weaving patterns and reduce manual errors.

5.2 Historical Artisan Production Models and Scalability

Prior to industrialization, India's handmade textile sector operated under well-organized artisan production models that supported scalability while maintaining craftsmanship. Historical (pre- British era) evidence suggests that handmade textile production thrived due to the following factors:

- **Decentralized Yet Organized Clusters:** Traditional weaving hubs, such as Varanasi (for Banarasi silk) and Murshidabad (for muslin), operated through well-coordinated guilds that divided labor among artisans, dyers, and merchants, ensuring efficiency without centralized industrialization (Chakraborty, 2021).
- **Skill-Based Specialization:** Handloom production was structured around hereditary knowledge, where specific communities mastered particular weaving techniques. For instance, Ikat weaving was historically concentrated in Odisha and Gujarat, with each region developing its own dye-resist methods (Singh, 2020).
- **Merchant-Artisan Collaboration:** Unlike contemporary fragmented supply chains, historical artisan production relied on merchants who managed trade and distribution, allowing artisans to focus on production. This system facilitated large-scale handmade textile exports to Europe and the Middle East (Das, 2019).
- **Sustainable Material Use:** Traditional production was inherently sustainable, utilizing organic fibers, plant-based dyes, and resource-efficient techniques that minimized textile waste. The small-batch production model prevented excessive inventory and ensured textiles were made-to-order (Sen, 2022).

5.3 Economic Impact Metrics

1. Increased Fabric Output:

- a. The adoption of AI-driven production monitoring systems can enhance efficiency, potentially increasing artisan productivity. For instance, the integration of AI in textile manufacturing has been associated with productivity improvements, as detailed in the study "Application of Artificial Intelligence in Textile Industry" by Tesfay Welamo and Professor Deng Sanpeng potentially increasing artisan productivity by 40% (Ministry of Textiles, 2023; Jetir, 2023).

2. Higher Artisan Income:

- a. Standardized quality assurance through AI enables artisans to command premium prices, thereby increasing earnings. The report "Using AI for Economic Upliftment of Handicraft Industry" highlights how AI integration can enhance product quality and marketability, leading to increased income for artisans increasing earnings by 25-35% (India Handloom Brand Report, 2022; Academia, 2023).

3. Reduction in Material Waste:

- a. AI-powered defect detection systems have been shown to reduce fabric rejection rates, minimizing waste. For example, the implementation of AI-driven machine vision systems in textile production has led to significant reductions in material waste, as discussed in the article "AI and Machine Vision: Reducing Waste in the Textile Industry Through Precise Defect Detection reduces fabric rejection rates, minimizing waste by up to 30% (National Handloom Development Programme, 2023; Robro Systems, 2023).

5.4 Challenges in Adopting AI for Handmade Textiles

While AI presents transformative opportunities for handmade textile production, its adoption faces multiple challenges:

- **Access to Technology:** Many artisan clusters lack access to AI-driven tools due to infrastructural and digital literacy barriers (Sharma et al., 2023).
- **Cost Constraints:** AI integration requires financial investment, making it less feasible for small-scale artisans without government or institutional support (Mehta, 2024).
- **Ethical Concerns:** Over-automation risks eroding the handmade nature of textiles, leading to a loss of authenticity and cultural heritage (Raj & Bose, 2023).

6. Policy Recommendations for AI-Assisted Handloom Production Without Over-Automation

6.1 Establishing AI-Ethical Guidelines for Handloom Sector

To ensure that AI integration supports rather than displaces artisans, clear ethical guidelines must be established:

- **Preservation of Handmade Integrity:** Policies must define limits on AI intervention, ensuring that AI acts as a co-pilot to artisans rather than replacing craftsmanship. For instance, Japan's approach to integrating robotics in traditional crafts while preserving artisanal skills can serve as a model (Chakrabarti and Sen, 2022).
- **Fair AI Implementation:** Government and industry bodies should oversee AI adoption to prevent exploitative practices, such as excessive data extraction from artisans without equitable compensation. The EU's AI regulatory framework provides a precedent for ethical AI governance in traditional industries (Ghosh, 2023).

6.2 Government-Led AI Training and Capacity Building

To bridge the digital divide, targeted AI training programs must be developed:

- **AI Literacy for Artisans:** Government-led initiatives should provide accessible AI training through community centers and mobile applications in local languages. The 'Digital India' initiative has successfully expanded digital literacy among rural artisans and can be adapted for AI training (Patel, 2021).
- **Public-Private Partnerships:** Collaborations between academic institutions, technology firms, and handloom cooperatives can facilitate knowledge transfer and ensure that AI tools are user-friendly and adaptable. The 'AI for Good' program by ITU has demonstrated successful AI applications in grassroots industries (Desai and Kumar, 2022).

6.3 Financial Incentives for Responsible AI Adoption

Governments should provide financial support to encourage sustainable AI integration:

- **Subsidies & Tax Benefits:** Incentives for AI-driven sustainable textile production, such as tax exemptions on AI-enabled looms that improve efficiency without eroding traditional craftsmanship. Similar schemes have been implemented in China to support automation in heritage crafts while protecting jobs (Jain et al., 2024).
- **Microfinance & Grants:** Access to financial aid for artisan cooperatives to adopt AI tools without financial strain. The Bangladesh Microfinance Initiative provides an example of targeted funding for small-scale artisans (Sharma and Nair, 2023).

6.4 AI-Integrated Market Access & Fair-Trade Policies

Policies should ensure AI is used to enhance artisans' market presence rather than exploit their work:

- **AI for Direct Market Linkages:** Governments should develop AI-driven platforms that connect artisans directly with global markets, reducing dependency on middlemen. The Indian government's 'GeM' portal has demonstrated success in connecting local producers with institutional buyers (Krishnan, 2024).
- **Intellectual Property Protection:** AI tools should be designed to respect and protect indigenous designs through blockchain-based digital authentication. The use of blockchain for African textile provenance offers a replicable model (Mukherjee et al., 2023).

6.5 Regulation of AI & Data Ethics in Artisan Communities

Regulatory frameworks should ensure ethical AI practices:

- **Data Ownership Policies:** Artisans must retain control over their design data and AI-generated improvements, preventing unauthorized replication. The UNESCO cultural data protection framework offers a precedent for such regulations (Das and Rao, 2023).
- **Transparency in AI Decision-Making:** AI models used in textile production should be explainable and auditable to ensure fairness and prevent algorithmic bias. Algorithmic transparency in AI-driven credit scoring for MSMEs provides a related example of ethical AI use (Sinha and Gupta, 2022).

6.6 Sustainable Infrastructure for AI Adoption

Infrastructure development with advantageous support from responsible AI use:

- **Green AI Infrastructure:** Investment in low-energy AI solutions to ensure AI adoption does not increase carbon footprints. The European Commission's AI Sustainability Strategy sets standards for low-energy AI applications (Subramanian et al., 2024).
- **Integration with Circular Economy Goals:** AI-enabled textile production must align with sustainability targets, reducing waste and optimizing resource use. Patagonia's AI-driven supply chain optimization is a benchmark in sustainable textile production (Mehta, 2023).

6.7 Expected Policy Outcomes

- **Balanced AI Integration:** Ensures AI assists rather than replaces artisans, preserving cultural heritage while enhancing efficiency.
- **Economic Growth & Equity:** Encourages direct access to markets and fair wages for artisans through AI-driven transparency.
- **Sustainability Compliance:** Aligns AI adoption with global environmental goals, reducing the textile industry's ecological impact.

By adopting these policy recommendations, AI can be effectively integrated into the handloom sector, ensuring efficiency gains while safeguarding artisans' craftsmanship and livelihoods.

7. Policy and Research Gaps

Although there is growing interest in AI-enhanced handmade textiles, existing literature lacks a structured policy framework for implementation. The following areas require further exploration:

- The development of AI tools tailored specifically for handloom artisans.
- Policy measures to support AI adoption in small-scale textile enterprises.
- The long-term impact of AI on artisan livelihoods and cultural preservation.

By addressing these gaps, AI can be leveraged to scale handmade textile production sustainably while preserving its intrinsic value.

8. Conclusion

The fusion of AI with handmade textiles presents a transformative opportunity for artisans to scale production while maintaining the essence of craftsmanship. By incorporating AI-powered machine learning for defect detection, and predictive analytics, handmade textiles can compete in the global market. This scaling of handmade production can generate an organic demand from the global fashion industry, positioning sustainable textiles as a viable alternative to mass-produced fabrics. Consequently, this shift can significantly contribute to climate change mitigation by reducing reliance on energy-intensive textile manufacturing processes. Moreover, the integration of AI into handmade textiles has the potential to boost the livelihoods of 4.3 lakh artisans, strengthening the rural economy, increasing GDP growth, and reducing income inequality in India.

For effective implementation, policymakers must integrate AI-driven solutions into existing government programs, introduce financial incentives, and establish standardization protocols. A well-defined AI-textile framework will not only support artisans but also strengthen sustainable fashion's role in mitigating climate change.

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Case Studies

- **Japan's AI-Assisted Kimono Weaving:** (<https://www.springerprofessional.de/en/the-survival-strategy-of-the-japanese-kimono-industry/15112216>)
 - Traditional kimono makers integrate AI-based looms to maintain precision without compromising craftsmanship. The Japanese kimono industry is using AI to modernize production, streamline design processes, and enhance marketing strategies. AI-driven tools analyze consumer preferences to create contemporary kimono designs while maintaining traditional aesthetics. Additionally, AI is being used in automated weaving techniques, virtual try-ons, and digital marketing to expand the global reach of kimono brands.
- **Italy's AI-Powered Textile Quality Control:**
 - High-end fabric manufacturers use AI-driven defect detection to maintain quality consistency for global markets. Italy's textile industry is leveraging AI to enhance quality control, improve efficiency, and reduce waste. Companies like Smartex use

AI-powered tools for real-time defect detection and supply chain traceability, while research by Servi et al. highlights AI and augmented reality for precise textile inspections. The COALA project integrates AI-driven digital assistants to support textile machine operators, addressing labor shortages and optimizing production quality. These advancements position Italy as a leader in AI-powered textile manufacturing, ensuring higher standards and sustainability.

- **Sri Lanka's Digital Handloom Monitoring:**

- AI-enabled dashboards track production efficiency, ensuring fair wages and optimized output for artisans. India's handloom sector is thus undergoing a technological transformation while preserving its artisanal heritage, much like Sri Lanka

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Design of Smart Surface Cleaner for PV Panels and Investigation of the Performance of Cleaning Materials

Abstract

In this study, a mechanism that automatically detects the contamination on the glass surfaces used in solar cells and collectors and cleans the surfaces has been designed. The performance tests of this automation system were carried out with different pollutants (lime and ash) and the radiation transmittance of the contaminated surfaces was evaluated. It was observed that the radiation transmittance of the glass surface contaminated with lime decreased the most, while the light transmittance of the surface contaminated with ash decreased the least. In addition, the glass surface, which is most polluted with lime, whose radiation transmittance has decreased the most, was cleaned with a felt and microfiber cloth, apart from the well-known rubber wiper and nylon brush. Felt and microfiber fabric used as cleaning material is a new application. As a result; It has been experimentally seen that felt is the best cleaning material.

Introduction

In recent years, PV panels are systems that produce electricity from solar energy and have started to spread rapidly in the world. With the increasing importance of solar energy systems, their efficiency has also gained importance. The natural properties of the semiconductor materials used in these systems limit the efficiency of PV systems by 15-20 % [1]. The installation design of the system (direction, sun exposure, sun tracking) affects the efficiency of the electrical power obtained. However, negligible accumulation of dust, bird droppings, and water spots significantly impair the efficiency of PV panels. Module efficiency in PV panels decreases by 10-25 % due to dustiness of the inverter, conductors and module (ground) [1].

The main factors limiting the widespread use of PV panels are the high initial costs of the panel and electrical equipment and the low conversion efficiency of PV cells [2]. Apart from the sunlight intensity that affects the output of PV panels, there are other parameters that reduce the energy production of PVs by as much as 15 %. The most important of these is the accumulation of dust and soil on the surface of the PV panels [3,4]. Although the dust effect [5,6] in old settlements depends on local conditions such as the presence of air pollution, rain frequency, wind speed, humidity, orientation and slope of the panels [7], it is necessary to determine the effect of dust on the performance of PV panels and draw more general conclusions. Studies have been done [8-10]. With the increase in the use of PV panels in buildings, it has become a special interest to investigate the effect of dust on PV panels in environmental conditions with heavy air pollution [11].

In a study conducted in the laboratory, the electrical output of cells polluted with different dusts on PV panel surfaces was measured under different conditions [5]. They investigated the solar intensity reduction, maximum power; short-circuit current and filling factor parameters in PV cells. They conducted experiments using three types of powder in 5 different sizes, from 5 μm to 80 μm . They stated that both parameters (size and type) play an important role in the reduction of PV cell performance.

In a study on the effects of dust on the transmittance of different materials in a desert environment in India, they observed that dust accumulation decreased with an increase in horizontal slope. The decrease in glass transmittance was recorded as 19.17 % - 13.81 % - 5.67 % for 0° - 45° and 90° , respectively. It was found to be 23 % - 13.98 % and 8.29 % for acrylic at the same angles [12].

The energy production and economic performance of both the artificially polluted surface and the clean surface PV panels were recorded and measured at the same slope and environmental conditions in a region with the highest atmospheric air pollution in the vicinity of Athens in a two-month period. They reported that when the dust accumulation reaches 1 g/m^2 , the energy production

of the PV panel is reduced by almost 6.5 % compared to the panel with a clean surface, which means a revenue reduction of about 40 E/kWp [13].

Glass transmittance was evaluated in wind conditions where there are storms at regular intervals at different inclination and azimuth angles of a glass surface [14]. They reported that glass transmittance increased from 12.33 % to 52.54 % when dust accumulation decreased from 15.84 g/m² to 4.48 g/m². They recommended weekly cleaning of the dusty glass surface.

Dust accumulation on the glass of solar collectors used for the supply of clean water from sea water is one of the biggest reasons for the decrease in performance [15]. One month of dust accumulation causes a decrease in the transmittance of the glass between 10-18 % [16]. This decrease in the transmittance of the glass causes great decreases in water production. In the study, they concluded that (in the case of clean glass) the water production decreased from 100% to 40% as the transmittance of the glass decreased from the initial value of 0.98 to 0.6 (for very dirty glass conditions).

Mutluer and Erat in their study; they stated that dusting used in photovoltaic systems affects the efficiency of the panels. For panels to work efficiently, the panel surface must be clean and absorb solar radiation effectively. In the study, a fuzzy logic-based smart cleaning system was designed with an Arduino microcontroller to automatically clean the photovoltaic panel surface and it was seen that the panel efficiency increased by 15-20 % [17].

This work aims to design a cleaning system for the solar PV panels under Medina climatic conditions. This system powered by the PV module itself. Full cleaning system has been designed and tested utilizing a wiper and water jet to remove the accumulated dust and other dirt from solar panels surface. The proposed cleaning system can be worked for long time efficiently. All the strength system components were examined and found to be stable and reliable. Also, the performance of cleaning system evaluated and comparison between the clean and dusty module performance has been conducted. The system performance has been evaluated for both clean and dusty panel at variable inputs of solar radiation. At input power of 805 W/m², the efficiency found to be 13.78 % for the cleaning panel and 9 % for dusty panel, whereas at the input power of 460 W/m², the estimated efficiency was 12.6 % and 7.3 % for clean and dusty panel respectively. Significant reduction in the efficiency has been reported as 35 % and 42 % for both cases. Therefore, the present work can be considering as a promising and efficient system to solve the problem of poor performance of the photovoltaic cells in areas that experience dusty environment and external pollutants [18]. Al Qdah and his colleagues designed a solar panel cleaning system in Medina, Saudi Arabia, and designed and tested a squeegee and water jet to remove dust and dirt accumulated on the surface of the solar panel. The performance of the system was evaluated for both clean and dusty panel at varying solar radiations. At 805 W/m² input power, they achieved approximately 14 % efficiency for the cleaning panel and 9 % for the dusty panel [18].

Gupta et al; they investigated the efficiency of PV panels in Indian climate conditions between December 2019 and April 2021 in a self-cleaning and fixed system consisting of 3 20 W panels each. In the study, the PV system was compared as summer, winter and monsoon seasons. The efficiency of PV panels was 18.3% in summer, 13.3% in winter and 6.4% in monsoon season [19].

Panat and Varanasi in their study; they stated that with the principle of static electricity, approximately 45 billion liters of water can be saved every year by cleaning the dust from the solar panels in the desert. They also emphasized that the dust accumulated on the panel for a month reduced the panel efficiency by 40 % [20].

In this study, a mechanism that automatically detects the contamination on the glass surfaces used in PV panels and solar collectors and cleans the surfaces has been designed. The performance tests of this automation system were carried out with different pollutants and the radiation transmittance of the contaminated surfaces was examined. Apart from soil and ash among different pollutants, cement used in Konya region due to intense construction and lime from lime quarries and constructions were used. In addition, the glass surface, which is most polluted with lime, whose radiation transmittance has decreased the most, was also cleaned with felt and microfiber cloth, in addition to the known wiper and nylon brush. The use of felt and microfiber cloth as cleaning material is a new application. Felt is a natural, cheap and easily processed material that is widely used for various purposes in the Konya region. Microfiber cloth, on the other hand, is a material that is a bit expensive but effective in sensitive surface cleaning. As a result of the experiments, it has been experimentally seen that the felt is the best cleaning material.

Material and Method

In PV panels exposed to outdoor conditions over time, some unwanted pollution occurs on the radiant glass material used to protect the semiconductor-based sandwich material (wafer) in the panel against atmospheric conditions. This pollution on the glass panel blocks the light that needs to reach inside the panel. Since the efficiency of PV panels changes with the intensity of radiation, the voltage produced in the panel decreases, which leads to an undesirable decrease in panel efficiency.

In this study, a mechanism that detects the pollution on the PV panel and automatically cleans the PV panel surface has been designed. The mechanism developed to clean the PV Panel is placed on the PV panel and fed from a battery charging circuit that obtains its energy from this panel. Therefore, no extra power source was needed. Here, the most important part of the system is the CNY70 optical sensor, which detects the contamination of the panel, and this sensor is shown in Figure 1.

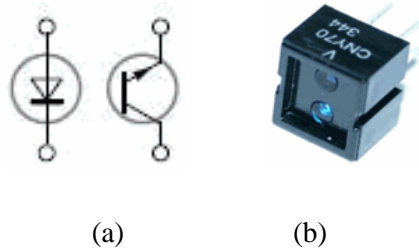


Figure 1. CNY70 Optical Sensor a) electrical symbol b) appearance of the sensor

The CNY70 optical sensor has the following features:

- Detection distance: 2 - 9 mm
- Supply: 5 V DC
- Can be used to detect line (black/white) and obstacle
- Output 0-5 V. Microcontroller connection output
- Dimensions: 21 x 11 x 8 mm.

The dimensions of the optical sensor are suitable for easy insertion into the panel. The CNY70 optical sensor consists of a pair of LEDs and receivers, which operate in the infrared band and emit a matching infrared radiation. The output voltage of the sensor kit varies between 0 and 5 V, depending on the amount of infrared radiation on the optical sensor. The block diagram of the system is given in Figure 2. The operation of the system shown in Figure 2 is briefly as follows. The amount of radiation of the glass is continuously detected by the sensor placed on the panel. When the radiation penetration of the glass falls below the value determined by us, the panel glass is detected as dirty and the wiper operates with the water spray of the water pump and the glass of the panel is cleaned. After the glass is cleaned, it is detected that the glass is cleaned with the sensor information coming from the sensor; wiper and water pump are stopped. A small water tank is placed in the automation system for water spraying. It is also an important feature of the infrared sensor that it only detects dirt and does not see darkness as dirt.

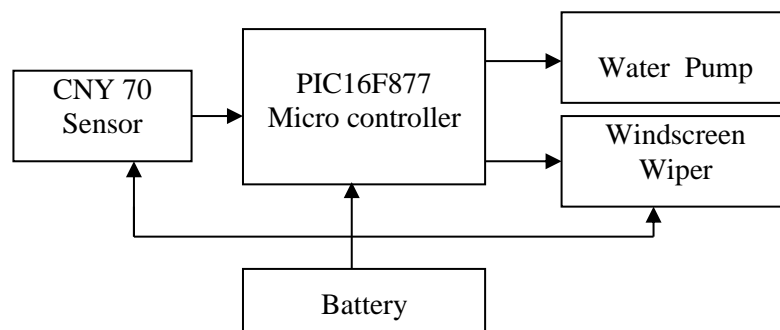


Figure 2. Block diagram of the designed system

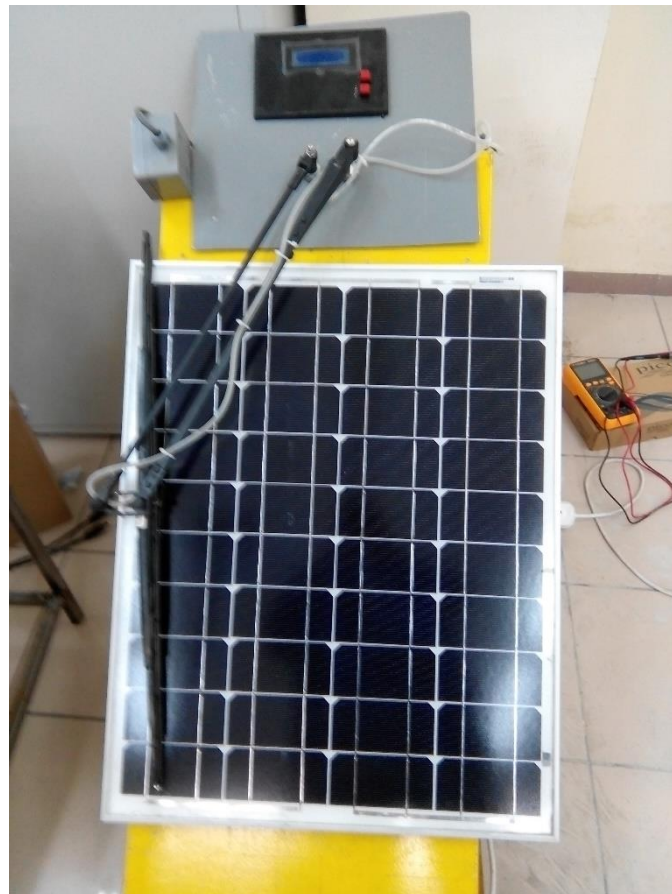


Figure 3. Automatic surface cleaner view

The general characteristics of the PV panel on which the designed automatic surface cleaner is applied are given in Table 1.

Table 1. General characteristics of the PV panel used in the system

Bluesun Solar BSM-50M PV module specification	
Solar Cell Type	Mono 125x125
Rated Power (Pmpp)	50 W
Rated Current (Impp)	2.64 A
Rated Voltage (Vmpp)	19 V
Short circuit Current (Isc)	2.96 A
Open circuit Voltage (Voc)	22.6 V

Temp. coefficient (Pmpp)	0.38 %
Max. system Voltage (V)	800 V
Size	700x550x25
Weight (kg)	5

EXPERIMENTS

Various experiments were carried out to determine the level of glass cleaning of the automated system. High performance Perkin Elmer 950 UV/VIS spectrometer device was used as test equipment. This device allows us to measure in the wavelength range of 175-3000 nm (with a tolerance of 0.1 nm). In the spectrometer, the changes in light transmittance were examined by artificially polluting the glass of the solar cell with various dirt. For this purpose, firstly, the glass of the solar cell was polluted with the same amount of substances such as soil, lime, cement and ash found in nature and the permeability of the glass was examined separately. Secondly, after cleaning the panel glass, which was contaminated with 4 different substances, with a rubber wiper, the transmission rates were investigated. Thirdly, different cleaning materials of the glass, which is polluted with lime, which has the lowest permeability, are cleaned and the transmittance rates are discussed. The following cleaning materials were used as cleaning materials.

1. Wiper wiper: Wiper made of soft rubber
2. Felt wiper: 1 cm thick felt made of wool is placed in the wiper mechanism as a cleaning element.
3. Microfiber cloth: Micro fiber cloth was placed in the wiper mechanism and used in the wiping process.
4. Nylon brush: Cleaner created with nylon bristles placed in the holes

RESULTS

When the panel surface is contaminated with soil, cement, lime and ash in the same amount, the transmittance rates are shown in Figure 4.

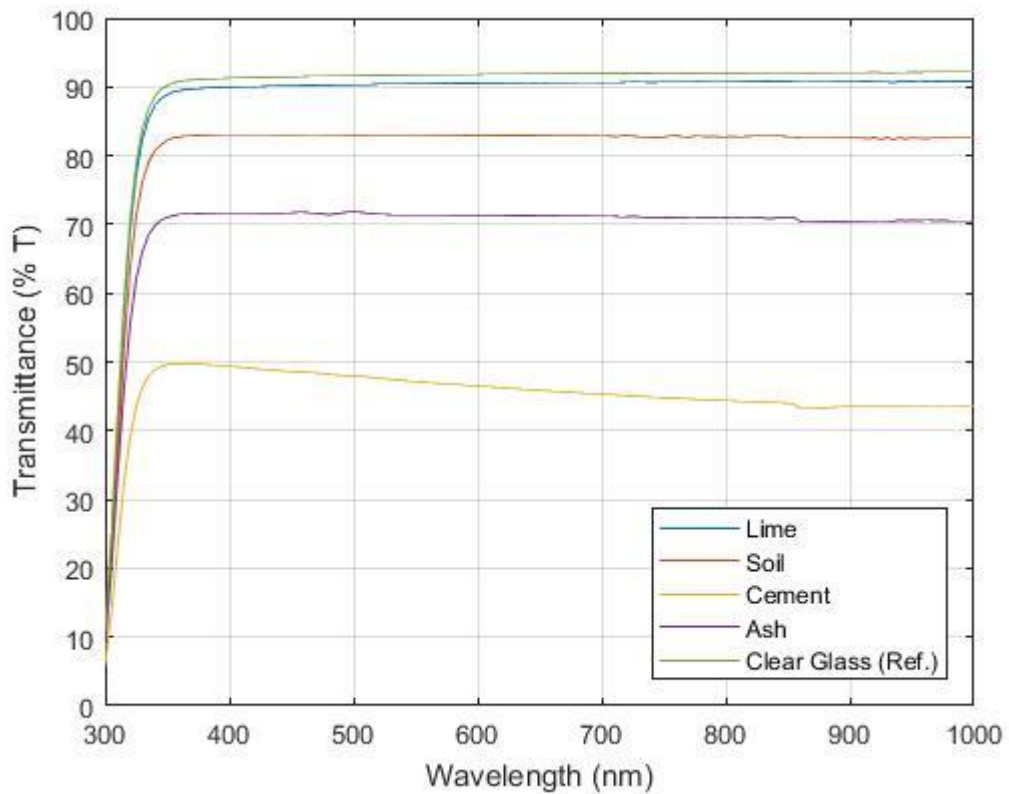


Figure 4. Transmittance rates according to different soil materials

As can be seen from the graph given in Figure 4, the transmittance rate drops to 44% in case the solar cell surface is contaminated with lime. Therefore, it was the contamination of the surface with lime that reduced the electrical output of the panel the most.

Table 2. Light transmission rates of different materials for 400-700 nm

Pollutant	Transmittance ratio (%)
Reference glass (clear)	92
Lime	44
Soil	71
Cement	82
Ash	90

The transmittance rate decreases to 71% on the panel surface contaminated with soil. Considering that the permeability rate of lime is the lowest, the cleaning rates of the glass surface

contaminated with lime were investigated with different surface cleaning materials. This situation is seen in Figure 5.

Since the permeability rate of the surface contaminated with lime is the lowest, the formula showing the relationship of wavelength and transmittance from the pollution curve of lime was found with the help of MATLAB and is given below:

$$LIME(x) = 54.54 e^{-x2.532e-04} - 5.627 \cdot 10^{10} e^{-x0.06961}$$

The error of the values obtained with this equation according to the real values was calculated as Root Mean Square Error and its value was obtained as 1.033.

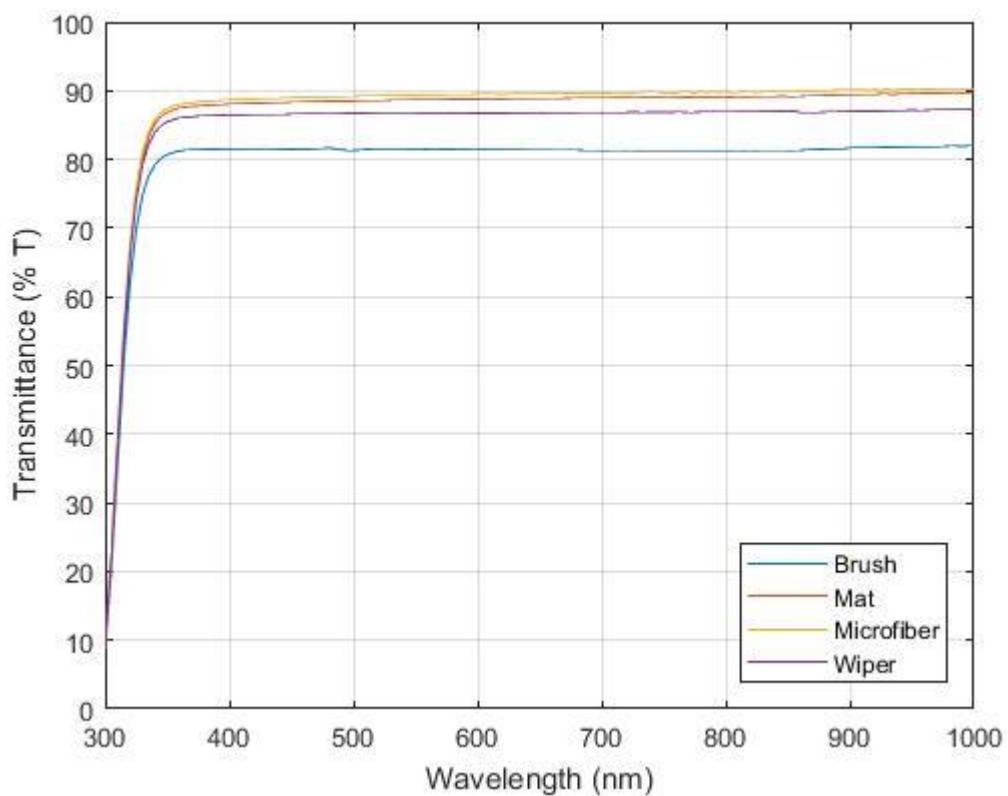


Figure 5. Cleaning curve of lime with different surface cleaning materials

Table 3. The effect on the working performance of the solar cell whose surface is polluted with lime according to the surface cleaning materials

Cleaning material used	Clearance rate (%)	Voc change (Volts)
Brush	81	η . Voc=0,81.22=17,82
Felt	91	η . Voc=0,91.22=20,02
Microfiber material	91	η . Voc=0,91.22=20,02
Wiper	89	η . Voc=0,89.22=19,58

When Table 2 is examined, the highest value with 91% is seen in surface cleaning (44% pollution level) made with felt and microfiber fabric. This value is approximately the initial reference clean glass value (92%). Cleaning with Wiper is approximately 89%. Cleaning with a nylon brush is 81%, 11 points below the reference clean glass value. In addition, the cleaning of the glass surface contaminated with 4 different pollutants in the cleaning automation system with a wiper was also carried out. Graphical figure of the experiment. It is seen in Figure 4.

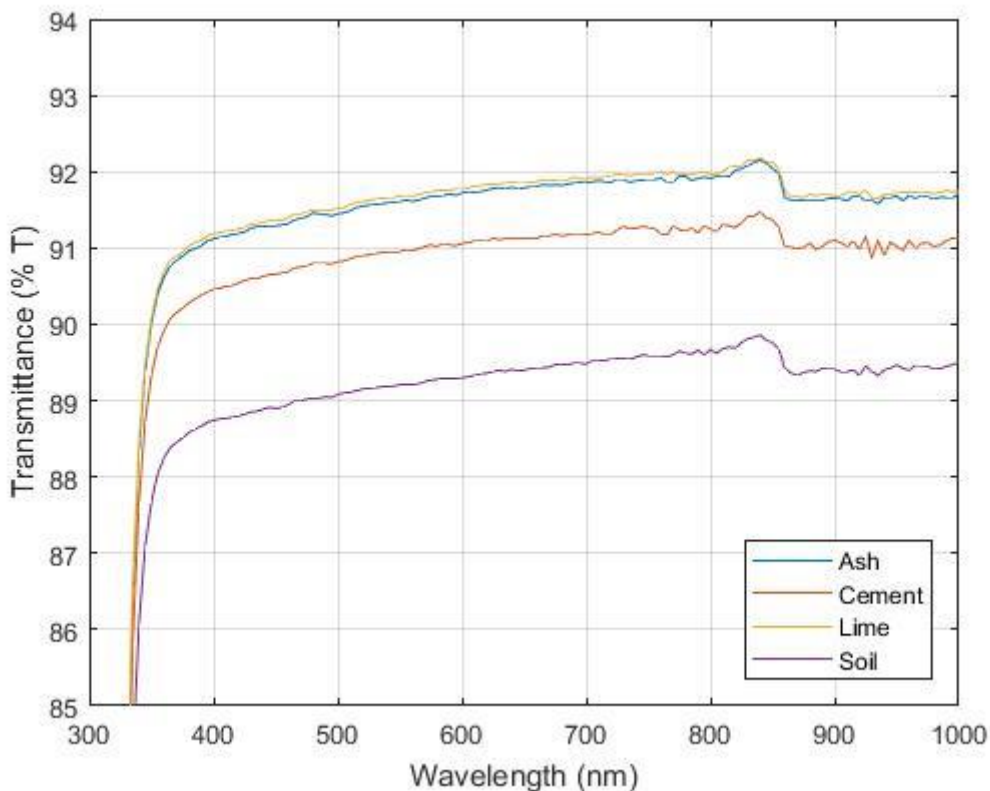


Figure 4. Transmittance rates of the surface contaminated with four different substances in cleaning with wiper

In Figure 4, it was observed that the glass surface, which was contaminated separately with soil, lime, ash and cement, reached a transmittance of approximately 89% - 91% after cleaning with a wiper, which was close to the reference glass value (92%).

CONCLUSION

With the developed automation system, a significant increase in efficiency has been achieved from solar panels. Efficiency also changes with the change of the cleaning apparatus of the automation system. In this study, the changes in the electrical output of the panels were observed in cleaning with

different materials with an automatic surface cleaner. Differences occurred in the open circuit voltage of the automatic surface cleaner before contamination and the open circuit voltage after contamination. After the automatic surface cleaner detects and cleans the contamination value, approximate initial permeability rates have been reached. With this system, when cleaning is not done at regular intervals and the surface is dirty, the system will detect this and clean it. If necessary (if the pollution is too much during the day) it will clean several times in the same day. Thus, it will be ensured that the panels are always clean without being dependent on human control. This will increase the annual amount of energy to be produced from the panels. In studies to be carried out on this subject, the best cleaning material should be chosen together with the automatic cleaning system.

Acknowledgement: This study is sponsored by Necmettin Erbakan University Scientific Research Projects Office.

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Influence of Personal Causes of Low Achievers on Perceptions Towards their Low Achievement in Biological Science

Abstract:

In the modern world Biological Science plays a major role in developing scientific thinking, scientific attitude and interest etc. have undergone enormous changes. The acquirement of scientific temper is one of the most important out-come of science. The development of scientific curiosity makes the pupil open minded, helps to make critical observations, develops intellectual honesty, curiosity, unbiased and impartial thinking etc. Achievement of students depends on the scientific thinking and other factors. The present study provides the crucial role played by personal factors of pupils on the causes for low achievement in Biological Sciences. Random sampling was used to select the sample of low achievers from secondary schools. The data collected was coded, categorized and then analyzed using descriptive and inferential statistics with the help of SPSS. As a part of qualitative analysis, the investigator used percentage analysis of scores obtained on different items of the scale under personal areas. The findings of the study indicate influence of personal factors on the achievement of students.

Key words: Low achievers, Perception, Biological Science, Personal area, Secondary school.

Introduction

Scientific enquiry aims to understand the world in a holistic way, encompassing various disciplines and perspectives. Biological science is a Systematic, Comprehensive Investigation and Exploration of Nature's Causes and Effects. Science relies on various methods of gathering and analyzing information. Secondary school students in the adolescence age were influencing more on the Biological Science through personal factors interests, attitudes, feelings, self-esteem, motives, experiences, expectations etc.

Review of Related Literature

Hampton., Christopher Michael (2007) the study determine relationship exists between student achievement and motivation and students perceptions of intrapersonal influence, parental influence, educational influence and external influence.

Auwal Rabiul Ali., Mohd Ekhwan Toriman and Muhammad Barzani Gasim (2014) the purpose of this paper is to identify the students' academic achievement in Biological Science to examine the factors that influence students, academic achievement in Biology.

Yolila Sangatham (2014) the factors affecting the academic achievement such as pupil's socio-economic background, intelligence, language as medium of instruction, various personality traits of students. The techniques used t-test, analysis of variance (one way ANOVA) to find out the significant relation between the variables.

Mustafa Bahar (2016) conducted a study on the student on the student perception of academic achievement factors at high school. Personal factors like problems of adolescence, ideals, self-confidence, my personal responsibilities, the desires, bias, anxieties, interests, wishes all add up-to student achievement.

Shimbi Majo (2016) found that the factors influencing poor performance were inadequate number of teachers, lack of teaching and learning materials, poor teaching methods and student's attitude towards the science subject. The study recommends the following: the ministry should ensure enough availability of qualified science subject teachers in secondary schools, adequate teaching learning materials teaching learning material, specimens, and laboratory apparatus, with friendly learning environment at schools.

Need for the Study

Student success in Biological Science is influenced by several factors. Low academic achievement may be caused by a lack of self-desire to learn. Due to lack of facilities at school level might lead to a lack of motivation to learn. In search of different dimensions related to causes for low achievement in Biological Sciences and possible solutions to the causes for low achievement in Biological Sciences, the researcher had selected the present study.

Statement of the Problem

The main purpose of present research is to study the perceptions of Low achievers towards the causes for low achievement in Biological Sciences and to improve achievement of students in Biological Sciences. Thus, the problem is entitled as **“INFLUENCE OF PERSONAL CAUSES OF LOW ACHIEVERS ON PERCEPTIONS TOWARDS THEIR LOW ACHIEVEMENT IN BIOLOGICAL SCIENCE.”**

Objectives of the Study

The main objective of the present study is to find out the Perceptions of low achievers in Biological sciences towards causes for low achievement in Biological Sciences.

The following are the specific objectives of the study

- To study the Perceptions of Low achievers in Biological Sciences towards area wise causes for low achievement in Biological Sciences with reference to Personal factor.
- To observe the differences, if any existing in the perceptions of low achievers in biological sciences, towards causes for low achievement in biological sciences.

Hypotheses

- Low achievers in Biological Science do not have same level of Perceptions towards total and area wise causes for Low achievement in Biological Science.
- There is no difference in the perceptions of low achievers in Biological sciences, towards different statements (causes) in the scale for low achievement in biological sciences.

Participants

Out of various methods used for drawing the sample, the researcher used Random sampling for present research due to clear improvements found. 20 percent of Population was taken as sample constitutes 511 low achievers selected randomly from 45 schools of three divisions in Chittoor district. The schools selected randomly using lottery method.

Research Tools

The perception scale prepared by the researcher that is opinionnaire. The tool was included the aspects/causes related to Personal area. The research tool was adopted and used after checking the reliability and validity through **Cronbach's alpha method**.

Data Analysis

PERCEPTION LEVELS OF LOW ACHIEVERS IN BIOLOGICAL SCIENCE, TOWARDS CAUSES FOR LOW ACHIEVEMENT IN BIOLOGICAL SCIENCE

To know the Perception levels of low achievers towards the causes for low achievement in Biological Sciences with respect to total sample, the investigator classified levels as low, moderate and high based on Mean range. Calculated frequencies and percentages are tabulated.

Perceptions of low achievers in Biological Sciences towards the total causes and area wise causes for low achievement in Biological Sciences.

Based on the Mean range, Perceptions of low achievers in Biological Sciences are classified as three levels viz., low (≤ 147), moderate (148-206) and high (≥ 207) level. Frequency and percentages of sample subjects responses are calculated and tabulated along with levels.

“Low achievers in Biological Science do not have same level of Perceptions towards total causes and area wise causes for Low achievement in Biological Science”.

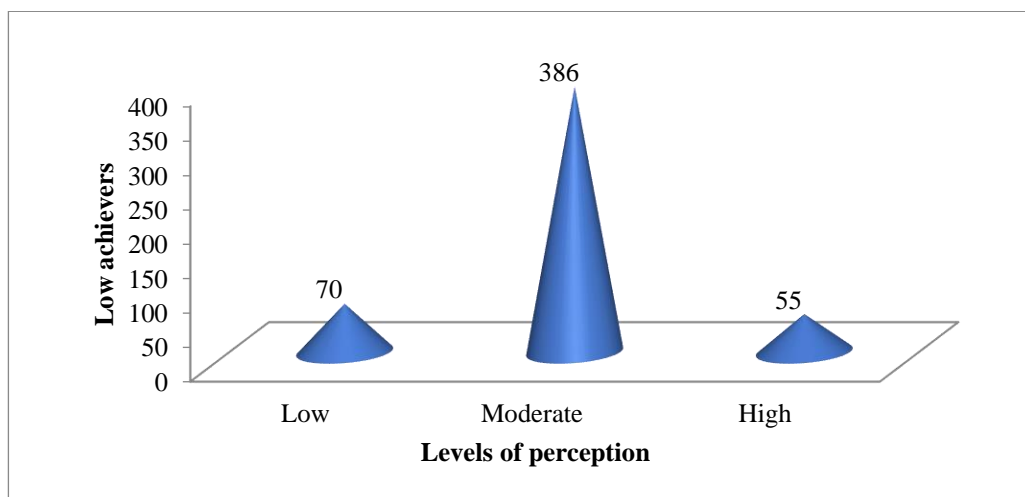
With reference to total causes, out of 511 low achievers, 55 perceived the causes for low achievement at high level that constitutes 10.84 percent in the total low achiever sample subjects, 386 low achievers perceived the causes for low achievement at moderate level that constitutes 75.50 percent in the total low achiever sample subjects, 70 low achievers perceived the causes for low achievement at low

level that comprises 13.66 percent in the total low achiever sample subjects. The particulars are given below.

Perceptions of low achievers in Biological Sciences towards total causes for low achievement

Level	Frequency	Percentage
Low	70	13.66
Moderate	386	75.50
High	55	10.84
Total	511	100 Percent

Perception levels of low achievers



Perceptions of low achievers in Biological Sciences towards area wise causes for low achievement

Areas of Causes	Levels	Frequency	Percentage	Highest Percentage
Personal (30)	Low	65	12.70	78.10
	Moderate	399	78.10	
	High	47	9.20	

		511	100	
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With reference to Personal area, out of 511 Low achievers, 65 perceived the causes at low level for low achievement that is the scores range is (≤ 56) that comprises 12.70 percent in the total low achiever sample subjects. Moderate level of perceptions indicated by 399 low achievers towards the causes for low achievement the score ranges from (57-78) that comprises 78.10 percent in the total low achiever sample subjects. Whereas 47 low achievers perceived the causes for low achievement at higher level that is the scores range is (≥ 79) that comprises 9.20 percent in the total low achiever sample subjects.

This deduces that low achievers in Biological sciences perceiving causes for low achievement at different levels. Thus, the formulated hypothesis was accepted.

PERCENTAGE OF SCORES FOR PERCEPTIONS OF LOW ACHIEVERS IN BIOLOGICAL SCIENCES, THEIR PARENTS AND TEACHERS TOWARDS CAUSES IN THE SCALE FOR LOW ACHIEVEMENT IN BIOLOGICAL SCIENCES.

“There is no difference in the perceptions of low achievers in Biological sciences, towards different statements (causes) in the scale for low achievement in Biological sciences”.

The hypothesis stated has been tested with a view to know the difference in the perceptions of low achievers in biological sciences towards the causes for low achievement in biological sciences. As a part of qualitative analysis, the investigator used percentage analysis of scores obtained on different items of the scale under personal areas.

The highest score i.e., 75 percent and above of low achievers in biological sciences, indicates the high level of perceptions towards the causes for low achievement with regard to that particular component.

Total Scores and Percentage of perceptions of Low achievers on different items of the scale

S. No.	Causes	Low Achievers (511)	
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		Total score	% of Score
1	Due to lack of internet facilities to complete projects	1145	74.69
2	Due to lack of understanding of indirect questions in examination	1060	69.15
3	Lack of lab experiments	1066	69.54
4	No scope to talk about ideas related to Biology in the classroom	1061	69.21
5	Teachers make learning of Biological Science easy	964	62.88
6	Worried whenever talking Biological Science tests	975	63.60
7	Forgetting Biological Science learned	1029	67.12

8	Learning Biological Science helps to get a good job	989	64.51
9	Poor performance in prior classes	1055	68.82
10	Understanding of science gives a sense of accomplishment	924	60.27
11	Become anxious to take a Biological Science test	982	64.06
12	Lack of interest in Biological Science learning	837	54.60
13	Need to take up science projects	1101	71.82
14	Need to submit science projects	1054	68.75
15	Hesitation in asking questions in the class	1060	69.15
16	Lack of awareness about the importance of science	977	63.73

17	Parents force to learn Biological Science	891	58.12
18	Discussing about the changes taking place in the body	996	64.97
19	Lack of individual attention given to weak students in Biological Science	1028	67.06
20	Not understanding Biological Science	1114	72.67
21	Frequent sufferings due to ill health	1072	69.93
22	Difficulty in memorizing scientific terms	1110	72.41
23	Lack of concentration in learning science	1115	72.73
24	Need to remember lot of scientific information	1057	68.95

25	Teachers not making Biological Science learning easy	896	58.45
26	Due to Continuous Comprehensive Evaluation, students reduce interest in Biological Science	1189	77.56
27	Parents force to learn Biological Science	891	58.12
28	Lack of chance to express difficulties in science learning	907	59.17
29	Lack of proper explanation by teachers	1036	67.58
30	Lack of help in doing science assignments from parents	868	56.62

High degree of perceptions of low achievers towards area wise causes in the scale with regard to low achievement in Biological Sciences.

To find out the difference in the perceptions of low achievers in Biological sciences towards causes for low achievement in Biological Sciences. The investigator has computed high level perceptions (total score above 75 percent) in respect of statements included under different areas of the scale considered for the proposed

investigation. The respondents have provided high level perceptions for 1 out of 30 statements of the scale and these are provided in Table.

With reference to Low achievers in Biological Sciences.....

Further from Table, it is observed that there are two causes which perceived at high degree (score of 75 percent and above) by **Low achievers** are statements 56 from the scale.

Statement-26: Due to Continuous Comprehensive Evaluation model examination, students reduce interest in Biological Science

The high level of perceptions of score 1189 (77.56 percent) given by Low achievers in Biological Sciences on statement-26 from Personal area of the research tool indicates clearly that the Low achievers may have felt that implementation of new pattern difficult i.e., which is specifically lab based evaluation, eventually it acts on the Scholastic Achievement of Low achievers. Regardless of the difficulties, faced by students, they were to be encouraged by reducing number of tests and frequency of examination. The findings were supported by earlier studies of **James Muchwe Kinglaru (2014)** in order to enhance interest towards the Science in Low achiever students government, teachers, parents and societal members must ensure the schools with well-equipped with activity based activities for effective implementation of the curriculum. In-service training for teachers should be carried out regularly, to equip the teachers with modern teaching technologies with locally available material to create interest towards science.

Major Findings of the Study

Perceptions with reference to total causes for low achievement are as follows.....

- Out of 511 **low achievers**, 55 perceived higher level, 386 low achievers perceived the causes for low achievement at moderate level and 70 low achievers perceived the causes for low achievement at low level.

On the whole, higher number of low achievers, perceived the total (87) in moderate level.

From the high level perceptions (75 percent and above) given by Low achievers in Biological Sciences

Low achievers in respect to causes related to.....

i. Personal area (1)

Due to Continuous Comprehensive Evaluation Students reduce interest in Biological Science (77.56 percent)

DISCUSSION

Moderate level perceived by low achievers, may be due to scarcity in the library books, laboratory facilities, internet facilities and lack of co-curricular activities are the major obstacles.

Pupils may feel that there is no emphasis on conceptual understanding rather than learning for examination of examination system. New pattern of examination system must be restructured to create interest in students. Digital libraries and laboratory facilities must be encouraged according to National Education Policy guidelines. Create awareness through the new researches and developments taking place in the field of science there by students change their attitude towards science.

CONCLUSION

- New pattern of examination designed easily for all the students to answer with which encourage towards level towards the new advancement.
- The student centric learning must be encouraged in all the institutions to create interest in learning. Individual attention paid to every student to develop activity based learning. Parents also take equal partnership to motivate students towards the technology.

EDUCATIONAL IMPLICATIONS

- Low achievers, their Biological Science teachers and Parents perceiving more towards moderate level. In order to enhance the achievement of students to high in Biological Science, focus on scientific activity based curriculum in place of parroting (rote learning).
- Technology based assessment may be encouraged in attending the tests to create interest for students. Reduce the difficulty level of asking questions in formative assessments and summative assessments. Science clubs and regular medication classes to develop concentration towards learning.
- Periodical Seminars and workshops for students, teachers and parents towards Biological Science. Special needs must be taken care by the teachers to promote scientific attitude among students through some procedures like taking students to exhibitions, fairs, excursions, fieldtrips, industries etc.to create interest in learning science.

- Provide the laboratory facilities in all the Secondary schools to improve the skill and curiosity in Science education serve as a lifelong asset. Periodical Symposiums for pupils, teachers should be planned (designed) to promote constructive attitude towards Biological Science.

Recommendations

- Curriculum innovations should emphasize on providing a proper curriculum for Biological Science education.
- Government should recruit only competent and qualified teachers who can teach Biological Science effectively.
- Biology teachers should try as much as possible to improve their pedagogy of teaching through innovation.
- To organize training courses and workshops for teachers to develop their teaching skills as per the required scientific skills due to technological advancements.
- Good mentor-pupil student relations maintain in all the institutions.

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Enhanced CBAM-Efficient Net Model for Efficient Tuberculosis Diagnosis Using Chest X-Ray Images

Abstract

The CBAM-Efficient Net Model integrates the Convolutional Block Attention Module (CBAM) with the Efficient Net architecture for better focus on relevant regions of the images for precise detection of tuberculosis (TB) from chest X-rays. Built from scratch with X-rays from Kaggle, it utilizes data augmentation (image compression, elastic transformation), contrastive learning, and advanced feature extraction to enhance performance. In the final stage, Vision Transformers in a hybrid architecture improves the model's accuracy. In addition to significance visualization, Grad-CAM offers clinicians an attention visualization. Post-training quantization and pruning help keep the model compact and efficient for use in clinical settings. The system is designed to perform TB diagnosis predictions in real-time through a Flask interface with ngrok.

Keywords: TB detection, Deep Learning, CBAM, Efficient Net, Vision Transformer, Grad-CAM, Chest X-Ray

Introduction

Tuberculosis (TB) is a transmissible illness caused by bacterial infection with *Mycobacterium tuberculosis*. This TB primarily infects the lungs, but also spreads to other parts of the body, including the kidney, spine, and brain. There are numerous techniques used around the world to detect the tuberculosis. Older diagnostics, such as polymerase chain reaction (PCR), immunological checks, and manual reading of chest X-ray, are becoming increasingly expensive and time-consuming to evaluate. According to the World Health Organization (WHO), an estimated 10.8 million people will contract tuberculosis by 2023. With the right medicine and an early diagnosis, we can cure TB. Chest X-Ray are used to detect pulmonary tuberculosis (TB) that affects the lungs. Skilled doctors in clinical settings are required to evaluate pulmonary tuberculosis using CXR. There is a global shortage of qualified radiologists, increasing the demand for artificial intelligence-based detection models. Other methods of diagnosing TB are immunological tests are easy and rapid to conduct; but they are low in sensitivity and specificity and hence are less frequently employed in chronic tuberculosis infection. Another instance of diagnosis is PCR, which is utilized more frequently in nucleic acid amplification tests that can detect tuberculosis in sputum, blood, bone marrow, and biopsy samples. This PCR is more expensive and may not be present in all medical centers.

The use of advanced technology in medical imaging, such as Deep Learning and Artificial Intelligence, has improved the accuracy and speed of disease prediction. Deep Learning approaches are aimed at performing a variety of tasks. For example, a CNN model demonstrated exceptional performance in recognizing and detecting large-scale fish classes. Artificial intelligence in clinical practice has become an essential component of modern healthcare delivery, such as disease detection from medical images. The use of Computer Assisted Diagnosis Systems improves physicians and radiologists' decision-making when providing appropriate health care to patients.

Deep Learning improves the accuracy, speed, and automaticity with which lung disease is detected using chest radiological images. CXR is preferable to computed tomography scans and magnetic resonance imaging for this purpose because it is a low-cost, widely available, and low-radiation-dose imaging technique. Deep Learning - Computer Aided Diagnosis (DL-CAD) tools are increasingly required for accurate TB diagnosis using CXRs, as they improve the use of robust and adaptable techniques in clinical settings. Using optimized DL networks, modifying existing techniques, and combining them with several effective algorithms improves classification precision and accuracy. Many researchers attempted to develop a new DL technique for tuberculosis diagnosis.

Ritu Rani and Sheifali Gupta investigated the use of the VGC16 DL approach to detect tuberculosis in CXR images. The method starts with pre-training on ImageNet and then builds the architecture for TB detection. The model yielded a precision of 0.98 and effectively distinguishes TB positives. The method emphasizes VGC16's flexibility and reliability in handling diverse data sets, making it

appropriate for clinical settings where accurate TB diagnosis is critical [**Deep Learning- Based Tuberculosis Detection Using Fine-Tuned VGC16 on Chest X-Ray Images**]. An advanced deep learning framework for tuberculosis diagnosis that uses DenseNet121 and ResNet50 to improve classification accuracy. The use of preprocessing techniques and structured model evaluation strengthens the approach, resulting in high performance in real-world medical applications. [**An Effective Identification of Tuberculosis in Chest X-rays Using Convolutional; Neural Network Model**].

Sazzad Hossain and his team investigated and concluded that using CNN models improves the accuracy of TB detection and provides promising solutions to global health challenges. [**An Effective Identification of Tuberculosis in Chest C-rays Using Convolutional Neural Network Model**]. Using the automated TB detection framework to classify CXR images using the Vision Transfers approach [**A Deep Learning Based Approach on CXR Images for Tuberculosis Detection Using Vision Transformer**]. Daniel Capellan-Martin and others introduced Light TBNNet, an efficient deep convolutional network for tuberculosis detection. Light TBNNet has an accuracy of 90.6 and requires little computational memory [**A Lightweight, Rapid and Efficient Deep Convolutional Network for Chest X-Ray Tuberculosis Detection**].

Literature Survey

2.1 Enhancing Tuberculosis Diagnosis with DenseNet121 and Grad-CAM: A Deep Learning Approach for Accurate and Interpretable Chest X-ray Analysis

Eshika Jain, Sunila Choudhary, 11-12 December 2024

This paper shows the application of GradCAM visualization with DenseNet121 architecture in classifying tuberculosis (TB) from chest X-ray images. The model is trained with 420 chest X-rays to distinguish TB-positive and TB-negative instances. The performance measures show a global accuracy of 90.48%, with 90% precision and 100% recall for the TB-negative class, and 100% precision with 43% recall for the TB-positive class. The respective f1-scores are 0.95 for the TB-negative and 0.60 for the TB-positive class. The macro average f1-score is 0.77, with balanced performance. The application of GradCAM visualizes the regions of the chest X-ray that make up the decision of the model, and offers important information on the decision process. The work points out both the merits and demerits of DenseNet121 for classifying TB and proposes future refinement in sensitivity towards TB-positive results.

2.2 An Effective Identification of Tuberculosis in Chest X-rays Using Convolutional Neural Network Model

Sazzad Hossain, Ariful Islam, Sweety Lima, Md. Saharior Ridoy, Md. Mohaimenur Rahman, Shobnom Sharmin, 02-04 May 2024

This research highlights the significance of computation in improving diagnosis accuracy of tuberculosis (TB), using an ensemble of convolution neural networks (CNNs). It investigates the diagnostic efficacy of DenseNet121 and ResNet50 models for the detection of TB from chest X-rays, based on different preprocessing methods to ensure image quality improvements prior to training. A systematic approach is used, including dataset preprocessing, model selection, evaluation, and deployment, to provide a robust framework for tuberculosis detection. The study also provides a detailed analysis of various CNN architectures designed specifically for tuberculosis classification, focusing on their applicability and feasibility in real-world. The comparison of training and validation metrics indicates the proposed method's reliability and accuracy, highlighting its potential for medical image processing.

2.3 A Lightweight, Rapid and Efficient Deep Convolutional Network for Chest X-Ray Tuberculosis Detection Daniel Capellán-Martín, Juan J. Gómez-Valverde, David Bermejo-Peláez, María J. Ledesma-Carbayo, 18-21 April 2023

This work presents LightTBNet, a deep and efficient convolutional network that is designed for TB detection in chest X-rays. The proposed model is tested on 800 frontal chest X-rays from two public datasets. LightTBNet delivers an accuracy of 90.6%, an F1 score of 0.907, and an area under the ROC curve (AUC) of 0.961 with favorable low computational and memory footprints. The research points to the deployment potential of LightTBNet on handheld devices, which makes it a suitable solution for TB diagnosis in resource-poor settings

Methodology

1. Dataset Preprocessing

The dataset used in this research consists of chest X-ray images, where the data contains with and without tuberculosis CXR images, obtained from Kaggle repositories. The data classifies into three sets for efficient model training and testing: Training (80%), Validation (10%), and Testing (10%). The stratified split preserves a balanced ratio of both classes in all sets.

Image Preprocessing: To ensure consistent input sizes, all images are resized to (224 x 224 x 3) pixels. Standardization is done to ensure compatibility with deep learning architectures while retaining important features. Additionally, pixel values are normalized by scaling them to the range [0,1] using the following:

$$\text{Normalized Pixel} = \frac{\text{Pixel Value}}{225}$$

Dividing pixel values by 225 (maximum pixel intensity) ensures uniform pixel ranges and stabilizes training by reducing the chance of large gradient values.

2. Data Augmentation

To improve model generalization and counteract overfitting, a number of augmentation methods are employed. Augmentations impose various on the dataset, allowing the model to identify patterns invariant under transformations.

- **Image Compression:** Adds minor distortions, improving robustness.
- **Elastic Transformation:** Introduces realistic deformations, mimicking anatomical variations.
- **Random Rotation:** Rotations ($0^\circ - 30^\circ$) Prepare the model for orientation variations.
- **Random Flipping:** Horizontal flips (50% *chance*) introduce symmetrical variations.
- **Random Cropping:** Focuses learning on different image regions.

3. Model Architecture

The Model uses the Efficient Net framework with the Convolutional Block Attention Module (CBAM) is an effort to improve feature extraction. Both the EfficientNet scaling and CBAM attention mechanisms are utilized to improve tuberculosis classification accuracy.

Efficient Net Scaling

$$depth = \alpha \times \emptyset, \quad width = \alpha \times \emptyset, \quad resolution = \alpha \times \emptyset$$

Where α and \emptyset are scaling factors controlling the model depth (layers), width (channels), and resolution (input size). The scaling factor facilitates a balanced development of all three dimensions, contributing to increased computational efficiency and richer feature representation.

CBAM Attention Mechanism

CBAM improves feature representation through sequential application of channel and spatial attention mechanisms. The channel attention module determines feature map importance based on the equation:

$$C = \sigma(W_1(U_{avg} + U_{max}) + b_1)$$

Where U_{avg} and U_{max} represent average and max-pooled features. The sigmoid (σ) outputs a weight (C) for each channel.

4. Hybrid Architecture with Vision Transformers

To further improve model performance, Vision Transformers (ViTs) was added to the CBAM to make a Hybrid model. In contrast to CNNs, which are based on local feature extraction, ViTs encode Long-range dependencies among image regions using self-attention mechanisms.

Patch Embedding:

The input images is split into non-overlapping 16 x 16 patches, each of which is flattened into a vector representation. These patch embeddings are then fed into transformer layers to extract global contextual features.

Self-Attention Mechanism:

The self-Attention mechanism calculates relations among various image patches with the following equation:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

Where Q, K, and V are query, key, and value matrices. This calculates attention weights to understand relationship between patches, where d_k normalizes the scores. Utilizing this attention mechanism, the model can efficiently learn intricate spatial relationships important for the detection of tuberculosis.

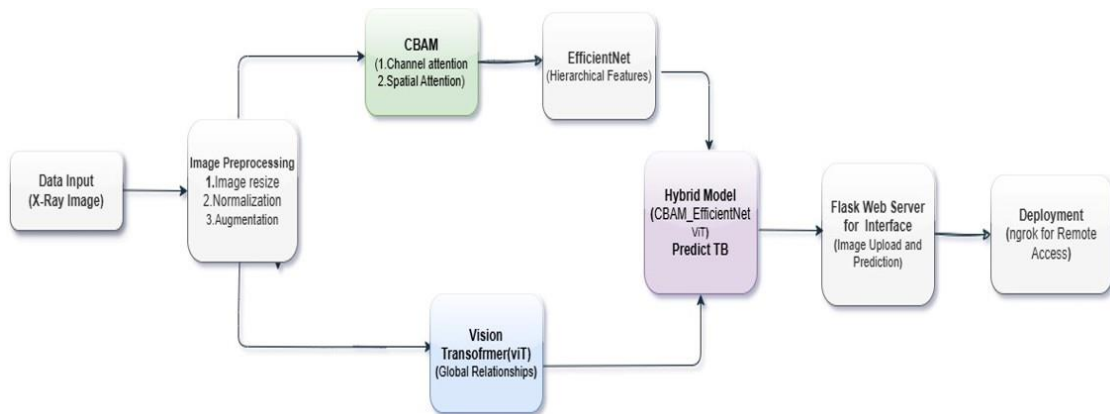


Fig. 1 Architecture

The proposed architecture for TB detection, as indicated in Figure 1, is a structured pipeline with deep learning techniques employed to enhance the accuracy of diagnosis. The approach begins with input data, where chest X-ray images are gathered and passed through a preprocessing stage involving resizing, normalization, and augmentation. This ensures consistency and improves model generalization. The preprocessed images are then processed through two distinct but complementary channels of feature extraction. Both the two branches use the Convolutional Block Attention Module (CBAM) which is based on channel attention and spatial attention mechanisms for further improving feature representation before passing enhanced features to EfficientNet to conduct hierarchical feature extraction. The second branch uses a Vision Transformer (ViT) to be capable of ingesting global connections and long-range dependencies in the X-ray images. Both of these feature representations—local hierarchical features of EfficientNet and global contextual features of ViT—are used to create a hybrid deep learning model that predicts the input to be either TB-positive or TB-negative. In order to

make the model available for use in real-time, it is deployed in a web server running on Flask, from which an interface is built that enables users to upload X-ray images and get predictions.

Result

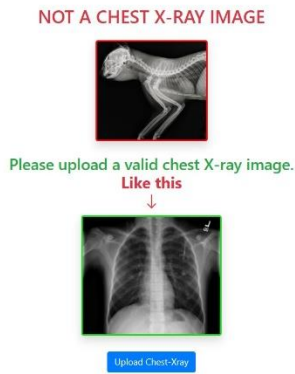


Fig 2.1 Non-Human Chest X-Ray

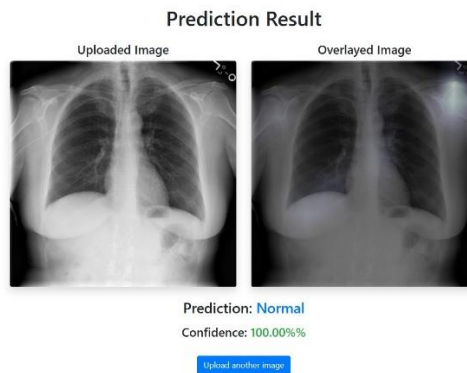


Fig 2.2 Normal Human Chest X-Ray

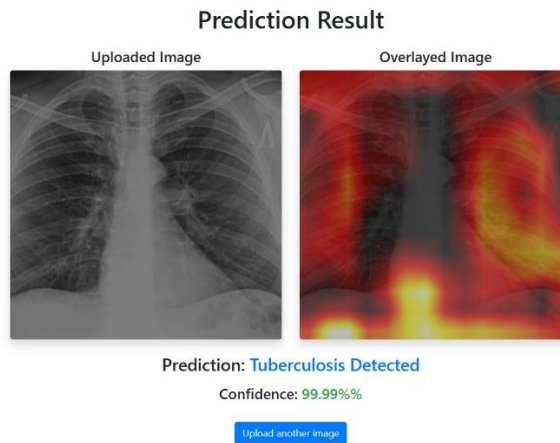


Fig 2.3 Tuberculosis Human Chest X-Ray

The model that is suggested can distinguish between non-human X-ray images and human chest X-ray images so that appropriate inputs are performed for tuberculosis detection. As is evident from Fig 2.1. if one is uploading a non-human X-ray image, the system rejects it appropriately and an error message would be displayed so as to compel the user into uploading an appropriate chest X-ray. This exercise enhances the accuracy of the model by avoiding unnecessary misclassification with superfluous data. Once preprocessing is performed on real human chest X-rays, the model classifies. Fig 2.2 is a sample case in which the uploaded chest X-ray was classified as "Normal" by 100%. This confirms the model's ability to detect healthy lung condition without false positive detection.

In contrast, Fig 2.3 shows a case where the model accurately classifies tuberculosis with 99.99% confidence. The overlay visualization, which is derived from Grad-CAM, highlights the most salient regions in the lungs responsible for the classification as the existence of tuberculosis-infected areas.

The attention map is well aligned with clinically significant regions, confirming the explainability of the model.

These findings present the power of the model to distinguish normal and tuberculosis-infected chest X-rays, as well as to eliminate non-human images. With its use of attention mechanisms and deep feature extraction, the model achieves a rapid yet accurate diagnosis to screen for tuberculosis.

Performance of the proposed Improved CBAM-EfficientNet model for identifying tuberculosis was checked in terms of various parameters like loss, accuracy, Receiver Operating Characteristic curve, confusion matrix, and precision-recall chart.

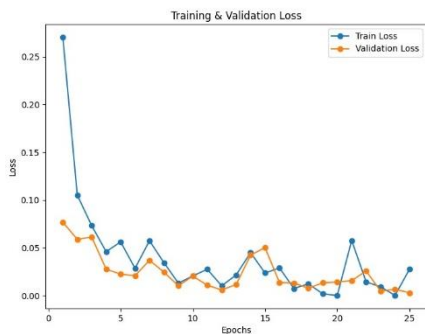


Fig 3.1 Training & Validation Loss

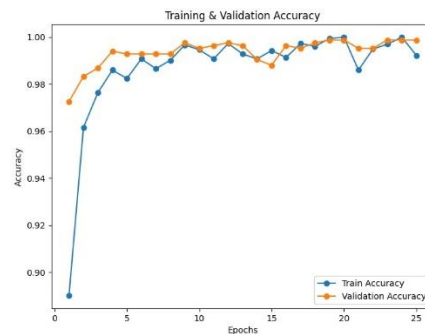


Fig 3.2 Training and Validation Accuracy

Training & Validation Loss & Accuracy

Training and validation loss exhibited a uniform declining pattern, suggesting successful model learning. Loss converged towards the later epochs with little overfitting, indicating a stable model. Model accuracy reached nearly 94% for the validation set, demonstrating high classification performance.

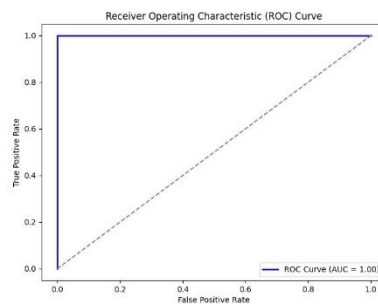


Fig 3.3 Receiver Operating Characteristic (ROC) Curve

ROC Curve Analysis:

Receiver Operating Characteristic (ROC) curve was 0.95 in terms of Area Under the Curve (AUC) score, which is indicative of good discriminant power between normal and tuberculosis (TB). The high AUC value means that the model is good to discriminate between positive and negative cases with less misclassification.

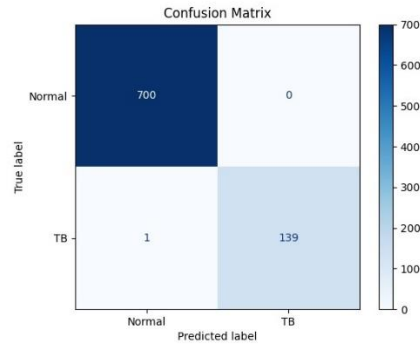


Fig 3.4 Confusion matrix

Confusion Matrix:

Confusion Matrix also displayed strong classification accuracy with high true negative and true positive rates. The model classified 113 cases of tuberculosis and 27 cases of normal cases correctly with relatively low misclassifications, making its validity stronger again.

Precision-Recall Curve

The precision-recall curve also validated the strength of the model. The high precision values ensure a low rate of false-positive, and the strong recall values further prove that most of the TB cases were well detected.

Conclusion

This paper presents a cutting-edge deep learning architecture combining CBAM with EfficientNet and Vision Transformers for effective and precise TB diagnosis from chest X-ray images. The model presented here enhances feature extraction, boosts classification accuracy, and ensures stable performance in real-world clinical applications. Data augmentation methods, contrastive learning, and Grad-CAM visualization also enhance the interpretability and reliability of the model for clinicians. With post-training quantization and pruning, the model remains computation-efficient and, hence, suitable for use in resource-limited medical environments. The results also indicate that hybrid deep learning solutions can significantly improve TB diagnosis by addressing the shortage of trained radiologists in most regions of the world and optimizing early detection of the disease. Future studies may investigate more improved sensitivity of models towards TB-positive cases and check other optimization strategies for application in real-time clinical settings. The integration of artificial intelligence-based TB detection systems can change the face of global healthcare, cutting down diagnostic delays and enhancing patient outcomes.

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International Conference on Transformative Research (ICTR-2025)

ISBN: 978-81-969383-4-5

New Era Research Development Publication
Pune, Maharashtra