International Journal of Electrical and Computer Engineering (IJECE)
Vol. 15, No. 1, February 2025, pp. 1218~1228
ISSN: 2088-8708, DOI: 10.11591/ijece.v15i1.pp1218-1228

Predictive modeling for healthcare worker well-being with cloud computing and machine learning for stress management

Muthukathan Rajendran Sudha[1], Gnanamuthu Bai Hema Malini[2], Rangasamy Sankar[3], Murugaaboopathy Mythily[4], Piskala Sathiyamurthy Kumaresh[5], Mageshkumar Naarayanasamy Varadarajan[6], Shanmugam Sujatha[7]

[1]Department of Computer Applications, College of Science and Humanities, SRM Institute of Science and Technology, Chennai, India
[2]Department of Computer Science, Shrimathi Devkunvar Nanalal Bhatt Vaishnav College for Women, Chennai, India
[3]Department of Electrical and Electronics Engineering, Chennai Institute of Technology, Chennai, India
[4]Division of Computer Science and Engineering, Karunya Institute of Technology and Sciences, Coimbatore, India
[5]Department of Electronics and Communication Engineering, K.L.N. College of Engineering, Sivagangai, India
[6]Lead Software Engineer, Glen Allen, USA
[7]Department of Biomedical Engineering, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Saveetha University, Chennai, India

Article Info

Article history:

Received Jun 15, 2024
Revised Sep 6, 2024
Accepted Oct 1, 2024

Keywords:

Cloud computing
Machine learning
Mental health
Physiological data
Stress management

ABSTRACT

This paper provides a new method for stress management-focused predictive modeling of healthcare workers' well-being via cloud computing and machine learning. The need for proactive measures to track and assist healthcare workers' mental health is highlighted by the rising expectations placed on them. Using various data sources, our system compiles information from surveys, social media, electronic health records, and wearable devices into a single location for analysis. Predictive models that predict healthcare workers' stress levels and well-being are developed using gradient boosting, a strong machine learning (ML) technique. This work is suitable for gradient boosting due to its resilience to overfitting and capacity to process many kinds of data. Healthcare organizations may improve the health of their employees by using our technology to detect stress patterns and identify the causes of that stress. It can use specific treatments and support systems to alleviate that stress. Widespread adoption and real-time monitoring are made possible by the scalability, flexibility, and accessibility of cloud computing infrastructure. This method shows promise in the direction of proactive solutions driven by data for controlling the stress of healthcare workers and improving their general well-being.

Corresponding Author:

Muthukathan Rajendran Sudha
Department of Computer Applications, College of Science and Humanities, SRM Institute of Science and Technology
Potheri, SRM Nagar, Kattankulathur, Tamil Nadu 603203, India
Email: mrsudha51@gmail.com

1. INTRODUCTION

In the coronavirus disease 2019 (COVID-19) epidemic, nurses are stressed. Over time, this tremendous pressure affects their health, quality of life, and patient care. Real-time stress detection and monitoring are crucial for early stress pattern diagnosis, burnout avoidance, and better patient-care outcomes in healthcare personnel [1]. Our proof-of-concept case study uses machine learning (ML) and artificial intelligence (AI) to estimate user stress levels based on heart rate, variability, and physical activity. This research explores Norwegian hospital workers' stress and cybersecurity activities. Hospital data is more susceptible to cyber assaults as the healthcare industry leverages technology to enhance patient care, and hackers may exploit the human component [2]. In India, the second COVID-19 epidemic has caused drug scarcity and increased morbidity. Due to the epidemic's suffering, mortality, and seclusion, COVID-19 has also affected health practitioners' mental health [3]. This cross-sectional research examines Indian healthcare professionals' mental health during the second COVID-19 pandemic. It addressed the significant inter-individual variability in ambulatory behavioral data by designing group-specific models of human outcomes [4]. Hospital staff had emotional and psychological difficulties after the epidemic, which might have affected their mental health [5]. Morphological properties of photoplethysmography (PPG) waveforms are examined to determine COVID-19-related stress and depression in first-line healthcare personnel. Stress and depression are modestly linked with significant systolic amplitude and early wave reflection characteristics. This method uses approaches to natural language processing (NLP) and artificial intelligence (AI) [6]. Drowsiness detection and prevention are an effective way to enhance hospital worker safety. Support vector machines (SVM) are used to anticipate utilizing hospital deployed internet of things (IoT) infrastructure data [7]. IoT infrastructure collects real-time data on ambient elements, work patterns, and employee physiological indicators. SVM models are trained on large datasets to discover sleepy patterns. Next, the model will be used in a hospital context to identify tiredness and intervene quickly. To evaluate the mediating impact of job satisfaction and presenters on the link between work-related stress and turnover intention in primary health care personnel [8].

The well-being and health of healthcare workers directly affect the quality of treatment for patients. Healthcare organizations often fail to handle employee burnout and stress adequately. Reactive and impersonal, traditional methods of healthcare worker stress management fall short. This initiative intends to transform healthcare stress management by creating a proactive and data-driven system. The system will forecast healthcare professionals' stress levels by analyzing data from several sources, including electronic health records (EHRs) and wearable devices, and then using cloud computing and machine learning. Recognizing and making sense of the many elements impacting health in such a complicated setting is the real problem. This approach aims to increase resilience, work health, and care delivery by offering early insights and personalized treatments.

The research proposes using cloud computing and ML to reduce healthcare worker stress. This novel stress management strategy is proactive and data-driven, unlike reactive methods. It advances the field by integrating electronic health records, questionnaires, wearable devices, and social media data. By centralizing different sources, the system gives a complete picture of healthcare worker well-being, enabling more accurate forecasts and focused interventions. It uses gradient boosting to show how advanced ML can predict healthcare worker stress. This algorithm can handle varied data sources and resist overfitting, making it ideal for modeling healthcare well-being. It advances prediction models for healthcare worker well-being, allowing early stressor diagnosis and proactive management. These algorithms predict stress and reveal well-being indicators, enabling healthcare organizations to give personalized help. It promotes data-driven stress management approaches for healthcare workers. The technology provides real-time analytics and personalized help to quickly improve the workplace for healthcare staff and patients.

Workplace stress increases burnout and lowers patient care in healthcare. Healthcare workers must be monitored for stress to offer appropriate solutions, but typical survey techniques may interfere with real-world duties [9]. Wearables can continually detect worker stress without invasiveness; however, context-specific behaviors and stress semantics may affect predictions. Using existing datasets, it uses shared stress representations to identify generalized stress in health professionals. Mental health issues such as stress, burnout, moral harm, depression, and trauma are more common among healthcare professionals and provide a general review of this problem [10]. These worries are made worse by public health crises, particularly considering new studies that show how the COVID-19 epidemic has affected healthcare professionals' mental health negatively. These risks to mental health are investigating the benefits of self-care practices, putting in place interventions supported by evidence, and instituting organizational measures to safeguard the mental health of healthcare workers. Healthcare workers endure enormous caseloads, little influence over the workplace, long hours, and changing organizational structures and processes [11]. These disorders cause stress and burnout, which harms professionals and patient care. There is a need to produce curricula that promote clinician wellbeing and self-care. This evaluation will assess the positive effects of mindfulness-based stress reduction programs on well-being and stress management in this demographic. Depression, anxiety, sleeplessness, and distress were reported by healthcare personnel reacting to the spread of COVID-19 at high rates in this survey research of Chinese doctors and nurses working in fever clinics or wards for COVID-19 patients [12]. Protecting healthcare workers is a top priority as part of public health efforts to combat the COVID-19 pandemic. Healthcare professionals exposed to COVID-19, especially women, nurses, and frontline workers, require urgent specialized treatments to support their mental health.

Healthcare workers' (HCWs) mental health during COVID-19 treatment settings has not been well researched in India. HCW in Karnataka State, India, is the focus of this investigation of its incidence and possible causal factors [13]. Volunteer healthcare workers who participated in COVID-19 training on mental health wellness were asked to fill out an anonymous online survey. Along with socio-demographics, other areas that are evaluated include occupational traits, issues connected to COVID-19, anxiety/depression, drug usage, suicidality, lifestyle, and home life. Daily bad emotions are managed by our emotional healthcare system, which uses facial expression recognition to make the system smarter and give services depending on user emotions [14]. Our facial expression emotion identification problem confuses positive, neutral, and negative emotions, making the emotional healthcare system relax people even when they do not have bad feelings. It uses electrocardiogram (ECG) stress detection to improve the relaxing service. Stress detection may solve facial expressions and emotion recognition misunderstandings to provide the service. Our findings show that stress monitoring improves the emotional healthcare system's performance. To stress management and cognition, including brain wave analysis, a person may see stress as uplifting or debilitating. An enhancing attitude reacts to stress better and is less negatively affected than a debilitating mindset. Stress attitudes may be changed by education [15]. It examines whether e-healthcare-based education may improve students' stress mentality. In healthcare, stress is the biggest issue. This work briefly reviews ML algorithms and IoT for stress prediction. Researchers have done a lot of studies on stress prediction [16]. It compares support vector machines (SVM) and k-nearest neighbor (kNN) accuracy and performance using perceived stress scale (PSS), ECG determined respiration (EDR), and ECG. Modern IoT ML techniques are covered in this study. Identifying stress sources, symptoms, and ML techniques has also been prioritized.

Modern culture is plagued by stress, which causes many physical and mental health issues. Effective stress management is essential as our lives get faster and more intertwined. This pioneering approach to challenge uses real-time stress monitoring via the IoT [17]. It proposes a comprehensive system that uses IoT sensors, powerful data analytics, and ML to measure and manage stress continuously the system's ML model adjusts itself based on user-specific stress patterns to estimate real-time stress levels. The feedback and personalized advice include deep breathing exercises and lifestyle changes. The body's reaction to stress may affect chronic illness sufferers' health. Although time-consuming and limited, self-assessment questionnaires remain the gold standard for stress evaluation [18]. Patients may reject stress estimate models that involve facial analysis, speech recognition, thermography, and electrocardiography. A distributed computing platform-based multichannel detection system employing PPG signal processing methods is suggested in this work to extract numerous physiological data. Body temperature and galvanic skin response acquisition were incorporated for the fuzzy logic stress estimate model. Covid-19 has aggravated HCW mental health because of an exponential growth in workloads and stress. Studies have shown that stress levels affect heart rate variability (HRV) [19]. It employed HRV to assess physician stress from the epidemic. Their perceived stress score questionnaire answers determined their elevated stress levels. Clinicians reported severe chronic stress in 40% of cases and moderate chronic stress in the rest. Our design combines graphical technological literacy with image processing to alleviate IT professional stress [20]. Our system improves on old stress discovery systems that tried to avoid live discovery and specific comforting by including periodic worker analysis and live invention to identify workers with physical and compressive load issues and suggest stress-management methods by outfitting periodic check forms. Our approach emphasizes stress management to create a stress-free workplace and relieve employee strain.

Stress issues are frequent among IT workers nowadays. Employee stress rises with changing lifestyles and work cultures [21]. Despite many sectors and corporations offering mental health plans to improve workplace culture, the situation is out of control. It uses ML to analyze stress patterns in working individuals and identify the elements that greatly influence stress levels. Data from the mental health survey 2017 of information and communication technology (ICT) workers was used after data cleaning and preprocessing the model using machine learning. It compared the accuracy of the models above. Boosting was the most accurate model. Gender, family history, and occupational health benefits were shown to impact stress using decision trees. These findings allow companies to focus on stress reduction and staff comfort. Most stressed workers say their project managers provide hefty assignments without acknowledging their discomfort. This project will automate task allocation based on stress measures and examine the relationship between workload distribution and workplace stress [22]. A voice-based chatbot to measure emotions and a gadget to check employee bodily metrics are used to determine stress. It transformed speech and bodily indicators from employees at work to stress levels. Design and specifics of our wearable IoT solution for harsh outdoor workplace health and safety. Since New Zealand's forestry business has the greatest deaths and accidents, concentrate on its needs. Consumer and professional wearables are unsuitable for forestry [23]. Due to their remoteness and ruggedness, forestry workplaces cannot use current networking infrastructure and cannot be permanently set up. IT workers nowadays often experience stress. Employee stress increases when lives and working cultures change [24]. This project will use IoT and supervised learning to study employee stress. After data cleaning and preprocessing, we trained our model using naïve Bayes, decision tree, and kNN algorithms. Comparisons were made to the model's accuracy. The kNN algorithm was the most accurate. Using the algorithm, significant stress variables were revealed. With these insights, companies may reduce stress and improve employee comfort.

User-relevant data in entertainment, social media, health, education, travel, cuisine, and tourism has been provided via recommender systems [25]. big data and IoT have quickly integrated technology into our daily lives, including smart healthcare. Innovative personalized eHealth and mHealth applications have emerged due to the widespread popularity of smartwatches, wearable gadgets, and biosensors. ML algorithms can read wearable data and advise healthcare professionals. Stress is a huge issue nowadays. Stress affects all ages and increases serious illnesses such as heart disease and depression [26]. Prevention is better than cure; therefore, early mental stress detection helps prevent heart attacks and depression. Stress causes changes in biological signals, including heat, electricity, impedance, acoustics, and optics, which may be used to assess stress. This paper designs and implements an IoT stress detection and categorization system. A wearable gadget measures physiological characteristics using three sensors: skin conductance, ECG, and skin temperature. A cloud server receives measurements from the user's phone [27]. AI systems analyze sensor data in the cloud to assess user stress. The user's phone displays the expected status and suggests stress-relieving activities. In emergency stress, the doctor receives a notification and may view the data via the cloud server. The real-time sensor data-based binary classification system achieves accuracy. Stress is an abnormal strain on daily living. Stress is one of the main causes of chronic health diseases. Thus, stress management is crucial in this age [28]. It discusses stress detection methods that employ low-cost wearable sensors and ML algorithms [29] to predict stress levels.

2. PROPOSED METHOD

Monitoring the health of these essential frontline workers is of the utmost importance in the modern healthcare system, where the demands placed on healthcare professionals are constantly rising. An innovative method that utilizes cloud computing, gradient boosting, and predictive modeling might completely transform stress management tactics in hospital settings, resolving this crucial problem. Predictive models that predict healthcare workers' stress levels and well-being are developed using gradient boosting, a strong ML technique. This work is suitable for gradient boosting due to its resilience to overfitting and capacity to process many kinds of data. Healthcare organizations may improve the health of their employees by using our technology to detect stress patterns and identify the causes of that stress.

2.1. Understanding the system architecture

This system is built around a solid foundation of data collected from various sources, including EHR, wearable devices, questionnaires, and more. Time off, patient loads, sleep habits, exercise levels, stress levels, and other vital life metrics are all covered by this data. Preprocessing is frequently necessary to guarantee the quality and trustworthiness of this raw data. It is crucial to clean the data, deal with missing values, and find outliers before further analysis. The feature engineering procedure follows the data preprocessing phase. At this stage, it will extract useful characteristics from the data that show how happy healthcare workers are.

Workload measurements, shift patterns, patient contact frequency, physical activity levels, sleep quality, and other pertinent elements might be included in these details. Developing reliable prediction models requires meticulous attention to detail in selecting and constructing these characteristics. The gradient-boosting advanced machine learning method is a key component of this system's predictive modeling. The nonlinear correlations between characteristics and outcomes and complicated, high-dimensional data are effectively handled by algorithms. To reduce prediction errors, gradient boosting techniques iteratively train ensembles of models to get better predictions. While training, validating, and deploying models, the system uses the scalability and flexibility cloud computing infrastructure offers.

Cloud computing [30] allows for the fast processing of massive amounts of data and complicated machine learning jobs by providing on-demand access to computer resources. Cloud-based solutions make integration with preexisting healthcare systems and procedures easier, providing accessibility and adaptability. It is crucial to evaluate and validate prediction models thoroughly to guarantee their reliability and generalizability. Accuracy, precision, recall, and area under the curve are metrics used to evaluate the model's performance. Preventing models from failing in real-world healthcare settings and making good generalizations to new data requires rigorous validation. The system's essential step is deploying trained models into production systems inside healthcare settings. Integrating with current systems, such as EHR or workforce management platforms, healthcare workers' well-being may be monitored in real-time.

Through the seamless integration of predictive models into healthcare organizations' everyday operations, stresses may be proactively identified and addressed, leading to healthier and more resilient staff. The system can track real-time model performance by seeking hospital managers and staff input. Retaining models regularly with new data keeps prediction models current and accurate. Healthcare companies may better address their employees' changing stress levels by instituting a culture of continuous improvement and adjusting their stress management practices accordingly [31]. Figure 1 shows how the proposed approach uses cloud computing to facilitate data processing, training models, prediction, and analysis. This, in turn, allows for efficient and scalable management of healthcare workers' well-being.

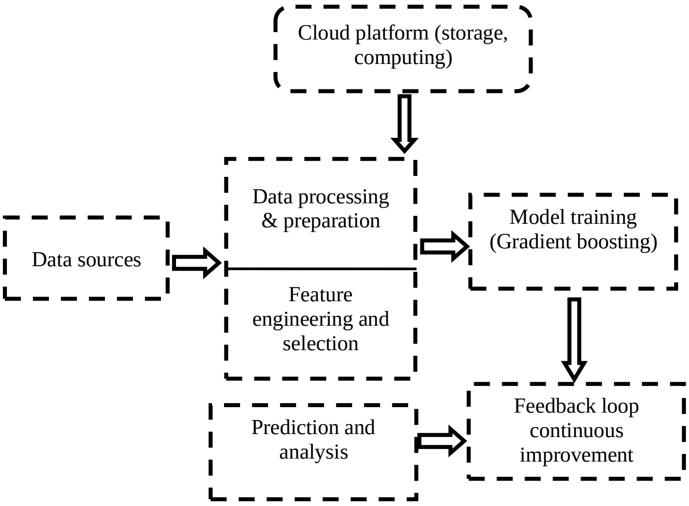

Figure 1. System architecture for proposed healthcare worker well-being

2.2. Gradient boosting model training process

The system's gradient boosting technique is described in further detail here:

a. Data preprocessing: Preprocessing is used to prepare the raw data for training models. This data comes from several sources, including wearable devices [32]. Among the responsibilities are encoding categorical variables, managing missing data, and normalizing numerical characteristics to ensure they are on the same scale.
b. Feature engineering: Important patterns and correlations are captured by engineering useful characteristics once the data is preprocessed. Wearable device data may provide insights into, among other things, physiological signals (like heart rate variability), activity levels (like step count), and sleep patterns (like length and quality of sleep). To increase the model's prediction performance, feature engineering seeks to provide it with useful input features.
c. Model training: The purpose of training a gradient-boosting model is to use the treated and modified features. Combining several weak learners, usually decision trees, into a single robust prediction model is the goal of the ensemble learning method known as gradient boosting. gradient boosting trains a new decision tree iteratively by fitting it to the residuals (errors) of the old trees. This iterative approach aims to improve the ensemble model's predicted accuracy by reducing the mistakes it makes. It is possible to fine-tune the model's performance by adjusting the gradient boosting algorithm's hyperparameters, including the learning rate, tree depth, and total iteration.
d. Model evaluation: Following training, the gradient boosting model is assessed using suitable criteria. Accuracy, precision, recall, F1-score, and area under the ROC curve (AUC-ROC) are common metrics for classification tasks. To ensure the model can handle new data and is generalizable, it may be tested using methods like cross-validation. The model assessment is all about finding out how well the model predicts healthcare workers' stress levels and, if needed, where they can be improved.
e. Model deployment: The gradient boosting model is used to make predictions on fresh data if it performs well during assessment. Using input variables like physiological data from wearables and other pertinent criteria, the deployed model may predict stress levels for healthcare professionals.
f. Feedback loop: For healthcare personnel who have been recognized as having high levels of stress, the predictions made by the deployed model might guide treatments or help. The gradient boosting model may be continuously improved using the feedback from these treatments and fresh data acquired over time. As healthcare workers' health and stress levels evolve, this feedback loop keeps the model current and flexible. The system's process is shown in Figure 2 flowchart. The data is first collected and then undergoes preprocessing and feature engineering to prepare it for training the model. The method

concludes with deploying the trained model for predictions and conducting performance evaluations. This systematic procedure guarantees the efficient use of data to provide forecasts about the health of healthcare workers [33].

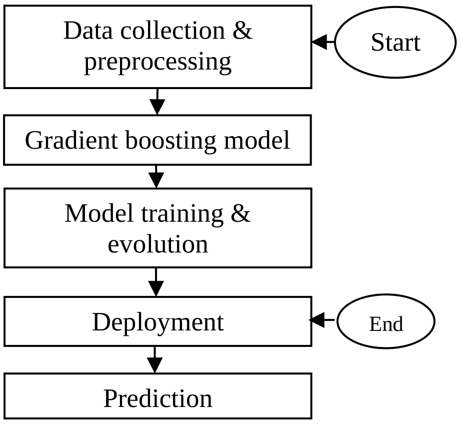

Figure 2. Workflow flowchart

3. RESULTS AND DISCUSSION

3.1. Results

The deployed solution utilizes cloud computing and machine learning to address the pressing problem of healthcare worker well-being, including stress management. The system provides proactive methods to aid healthcare workers' mental health and reduce stress via predictive modeling. Wearable tech and AI-powered algorithms keep tabs on various physiological and behavioral markers, letting users catch stress patterns early and help them cope better. To estimate the stress levels of healthcare workers, the system's predictive modeling component uses extensive data gathered from wearable devices and applies sophisticated machine learning methods such as gradient boosting. Healthcare businesses may protect their workers from possible stresses by using this predictive skill to identify them early on and manage them before they get worse.

The system's architecture is built on cloud computing, guaranteeing scalability, dependability, and accessibility. The system's ability to analyze and store data on the cloud allows it to manage massive amounts of data effectively, meet the growing demand, and provide healthcare companies with real-time insights. In addition to facilitating remote access for healthcare workers and allowing seamless interaction with current healthcare IT systems, cloud-based deployment promotes wider acceptance and use. The method might significantly alter healthcare worker wellness programs. Staff morale, productivity, and patient care may all be boosted when we take measures to combat stress and promote mental wellness.

Moreover, healthcare organizations can now make evidence-based decisions thanks to the data-driven system. This allows them to customize treatments and support methods to meet the specific requirements of their staff. The system is a huge step forward regarding healthcare personnel’s access to technological resources that promote their health and safety. It provides an all-encompassing strategy for stress management by integrating cloud computing with predictive modeling capabilities, leading to a robust healthcare workforce that is both healthy and efficient. The method might change the lives of healthcare providers and their patients if it is refined and adopted by many.

3.2. Discussion

As discussed in the debate, proactive stress management can transform healthcare workers' well-being. The solution enables scalable and tailored treatments based on data from wearable devices using cloud computing and machine learning algorithms. Job satisfaction, burnout reduction, and quality of patient treatment are all highlighted. Furthermore, it highlights the need to improve further and ensure wider adoption to get the best results. In sum, the conversation demonstrates how technology may positively impact healthcare workers' mental health, improving patient outcomes and creating a more resilient staff.

3.2.1. Healthcare worker dataset overview

Table 1 displays a dataset used to forecast healthcare workers' welfare. The user organizes the data, with many parameters recorded in each row. These features include HRV, steps taken, sleep length, stress level, skin temperature, activity level, respiratory rate, quality of sleep, and emotional well-being score. You can see whether the user is under a lot of stress (1) or not (0) in the "target variable" column. Using this dataset, machine learning models may be trained and tested to forecast the stress levels of healthcare workers according to their behavioral and physiological traits. The goal variable allows supervised learning to forecast stress levels, while the characteristics provide useful insights into possible causes impacting well-being. Healthcare worker assistance practices may be better understood and improved using this dataset.

Table 1. Health worker well-being data

User	Heart rate variability	Steps taken	Sleep duration	Stress level	Skin temperature	Activity level	Galvanic skin response	Respiratory rate	Quality of sleep	Emotional well-being score	Target variable
1	0.5	3000	7.5	3	32.5	0.8	4.2	16	7	8	0
2	0.8	5000	6.2	2	33.0	1.2	3.8	18	8	7	1
3	0.6	4000	8.0	4	32	1	4	15	6	6	1
4	0.7	3500	7.8	3	32.8	0.9	4.5	17	7.5	9	0
5	0.9	4500	6.5	2	33.2	1.1	3.5	19	8.5	8	1

3.2.2. Gradient boosting stress prediction

The stress levels predicted by a gradient-boosting model for different healthcare professionals are shown in Table 2. Each worker's actual or reported stress levels are kept in the "Actual stress level" column, while the model's predicted stress levels are shown in the "Predicted stress level" column. Users can see how well the model predicts healthcare workers' stress levels by comparing these two sets of data. If the anticipated and actual stress levels do not match up, it might indicate that the model needs some work. Better stress level projections and support measures for healthcare workers are possible thanks to this evaluation, which helps fine-tune the model to reflect the intricacies of worker well-being better.

Table 2. Healthcare worker stress prediction

User	Actual stress level	Predicted stress level
1	0	**0**
2	1	1
3	1	0
4	0	0
5	1	1

For various gradient-boosting model classification thresholds, the trade-off between the true positive rate (sensitivity) and the false positive rate (1-specificity) graphically represents the ROC curve in Figure 3. Where the model achieves high true positive rates while keeping low false positive rates across multiple thresholds, a curve closer to the top-left corner indicates stronger discriminating power. Higher values indicate greater discrimination between positive and negative cases. The AUC-ROC quantifies the model's overall performance. Essentially, the ROC curve aids in evaluating the model's class separation performance and choosing the best classification threshold. Figure 4 shows the trade-off between recall (sensitivity) and precision (positive predictive value) for various gradient-boosting model categorization thresholds.

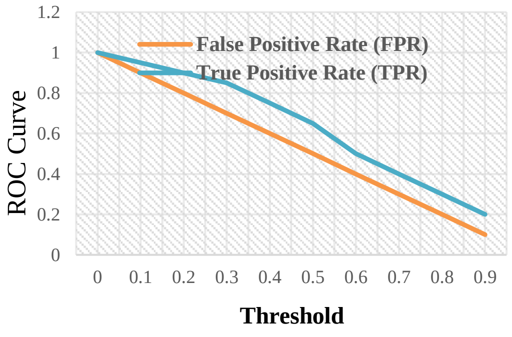

Figure 3. Gradient boosting model ROC analysis

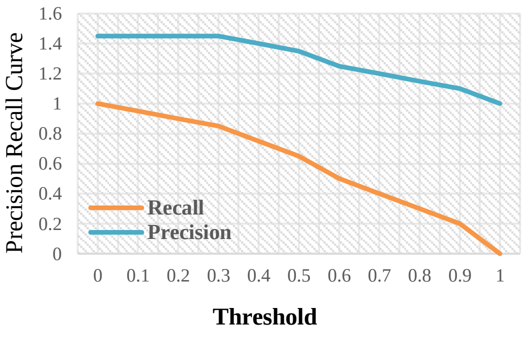

Figure 4. Precision-recall curve for gradient boosting model

Working with unbalanced datasets is very helpful. When the model successfully detects positive occurrences while limiting false positives, its accuracy and recall are greater, as shown by a curve closer to the top-right corner. The area under the accuracy-recall curve measures the model's overall performance, where larger values correspond to improved recall and accuracy. The precision-recall curve essentially aids in evaluating the model's capacity to categorize positive cases while accounting for false positives accurately.

Figure 5 graph shows the gradient boosting model's performance metrics across several iterations. The graph's points correspond to the model's AUC-ROC, F1-score, recall, accuracy, and precision at a particular iteration. It can monitor the evolution of the model's performance during training by keeping track of these measures throughout several iterations. Performance indicators should ideally converge to stable values or increase gradually over time to ensure that the model is learning efficiently. Changes to the model or training procedure may be necessary to improve performance if deviations or variations in the metrics point to problems like overfitting or underfitting.

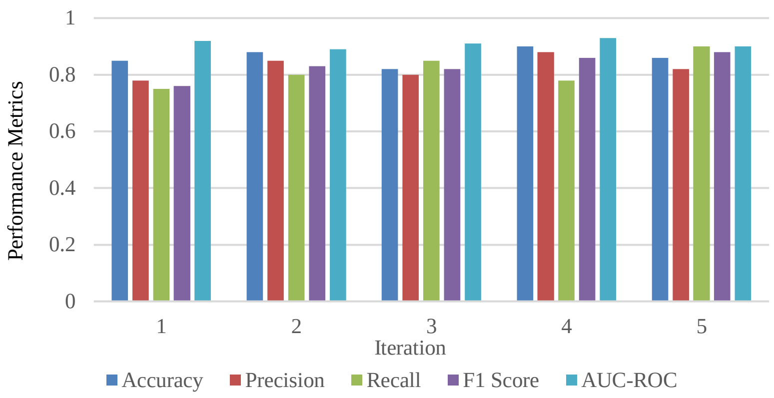

Figure 5. Gradient boosting iteration performance

3.2.3. Key benefits and implications

The key benefits and implications of this research include:

a. Proactive stress management: The healthcare industry may better protect its employees from impending stress by using predictive modeling to foresee possible problems and take preventative measures.
b. Improved patient care: The health and resilience of the workforce directly impact the quality of treatment that patients get. Healthcare personnel report more job satisfaction and better patient care when they experience less stress and burnout.
c. Resource optimization: Medical institutions may make better use of their computer resources for training and deploying models with the help of cloud computing infrastructure, which is both affordable and scalable.
d. Data-driven decision-making: Healthcare organizations may use data analytics and machine learning to make smart choices about stress management intervention prioritization and workforce optimization.

4. CONCLUSION

Finally, the established system has greatly advanced healthcare workers' well-being via proactive stress management. Technology provides healthcare providers with scalable, data-driven treatments customized to their specific requirements using cloud computing and machine learning. It helps reduce burnout and promote mental health by continuously monitoring behavioral and physiological signs using wearable devices. This allows for early diagnosis of stress patterns and prompt intervention. With algorithms such as gradient boosting, the system's predictive modeling component can accurately estimate the stress levels of healthcare workers. This allows businesses to treat and prevent stress proactively. Its cloud-based architecture also guarantees accessibility, dependability, and scalability, which makes it easy to integrate with other healthcare IT systems and encourages broad adoption. It must be fine-tuned and optimized even further to get most of the system going ahead. To cultivate a culture of wellness and resilience among healthcare workers, it is important to raise awareness and acceptance among healthcare organizations and professionals. More job satisfaction, less burnout, and better patient care are all possible outcomes of the system's potential to transform healthcare worker well-being programs. It might improve the healthcare system and lead to better results for doctors and patients if people keep inventing and working together.

REFERENCES

[1] R. G. Bangani, V. Menon, and E. Jovanov, "Personalized stress monitoring AI system for healthcare workers," in *2021 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*, Dec. 2021, pp. 2992–2997, doi: 10.1109/BIBM52615.2021.9669321.

[2] M. A. Fauzi, P. Yeng, and B. Yang, "Correlating healthcare staff's stress level and cybersecurity practices in Norway," in *2023 Intelligent Methods, Systems, and Applications (IMSA)*, Jul. 2023, pp. 235–240, doi: 10.1109/IMSA58542.2023.10217783.

[3] P. Gupta, S. Maji, and R. Mehra, "Predictive modeling of healthcare professional's stress based on XGBoost model," in *2021 IEEE 18th India Council International Conference (INDICON)*, Dec. 2021, pp. 1–7, doi: 10.1109/INDICON52576.2021.9691725.

[4] V. Ravuri *et al.*, "Group-specific models of healthcare workers' well-being using iterative participant clustering," in *2020 Second International Conference on Transdisciplinary AI (TransAI)*, Sep. 2020, pp. 115–118, doi: 10.1109/TransAI49837.2020.00026.

[5] M. Javierre *et al.*, "Quantification of stress and depression level posed by COVID-19 in first-line healthcare workers," in *2022 12th Conference of the European Study Group on Cardiovascular Oscillations (ESGCO)*, Oct. 2022, pp. 1–2, doi: 10.1109/ESGCO55423.2022.9931359.

[6] Kavyashree N and Usha J, "MediBot: healthcare assistant on mental health and well being," in *2023 7th International Conference on Computation System and Information Technology for Sustainable Solutions (CSITSS)*, Nov. 2023, pp. 1–5, doi: 10.1109/CSITSS60515.2023.10334083.

[7] B. J. Ganesh, P. Vijayan, V. Vaidehi, S. Murugan, R. Meenakshi, and M. Rajmohan, "SVM-based predictive modeling of drowsiness in hospital staff for occupational safety solution via IoT infrastructure," in *2024 2nd International Conference on Computer, Communication and Control (IC4)*, Feb. 2024, pp. 1–5, doi: 10.1109/IC457434.2024.10486429.

[8] L. Ning *et al.*, "The mediating role of job satisfaction and presenteeism on the relationship between job stress and turnover intention among primary health care workers," *International Journal for Equity in Health*, vol. 22, no. 1, pp. 1–9, 2023, doi: 10.1186/s12939-023-01971-x.

[9] J. L. Cahoon and L. A. Garcia, "Continuous stress monitoring for healthcare workers: evaluating generalizability across real-world datasets," in *Proceedings of the 14th ACM International Conference on Bioinformatics, Computational Biology, and Health Informatics*, Sep. 2023, pp. 1–5, doi: 10.1145/3584371.3612974.

[10] L. E. Søvold *et al.*, "Prioritizing the mental health and well-being of healthcare workers: an urgent global public health priority," *Frontiers in Public Health*, vol. 9, May 2021, doi: 10.3389/fpubh.2021.679397.

[11] N. Zholdas, O. Postolache, M. Mansurova, B. Belgibaev, M. Kunelbayev, and T. Sarsembayeva, "Development of a wearable monitor to identify stress levels using internet of things," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 33, no. 3, pp. 1486–1499, Mar. 2024, doi: 10.11591/ijeecs.v33.i3.pp1486-1499.

[12] J. Lai *et al.*, "Factors associated with mental health outcomes among health care workers exposed to coronavirus disease 2019," *JAMA Network Open*, vol. 3, no. 3, Mar. 2020, doi: 10.1001/jamanetworkopen.2020.3976.

[13] R. Parthasarathy, J. TS, T. K, and P. Murthy, "Mental health issues among health care workers during the COVID-19 pandemic – A study from India," *Asian Journal of Psychiatry*, vol. 58, Apr. 2021, doi: 10.1016/j.ajp.2021.102626.

[14] S. Tivatansakul and M. Ohkura, "Improvement of emotional healthcare system with stress detection from ECG signal," in *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, Aug. 2015, pp. 6792–6795, doi: 10.1109/EMBC.2015.7319953.

[15] H. Park and S. Hahm, "Changes in stress mindset and EEG through E-healthcare based education," *IEEE Access*, vol. 7, pp. 20163–20171, 2019, doi: 10.1109/ACCESS.2019.2895655.

[16] A. Jain and M. Kumari, "Prediction of stress using machine learning and IoT," in *2022 11th International Conference on System Modeling & Advancement in Research Trends (SMART)*, Dec. 2022, pp. 282–285, doi: 10.1109/SMART55829.2022.10046907.

[17] Asha, N. Patil, B. M. Preeti, and Laxmi, "Real-time stress level monitoring using IoT," in *2023 International Conference on Integrated Intelligence and Communication Systems (ICIICS)*, Nov. 2023, pp. 1–4, doi: 10.1109/ICIICS59993.2023.10421694.

[18] G. Ribeiro and O. Postolache, "New approach for stress assessment based on healthcare ecosystems," in *2023 IEEE Sensors Applications Symposium (SAS)*, Jul. 2023, pp. 1–6, doi: 10.1109/SAS58821.2023.10254045.

[19] A. Hendryani, D. Gunawan, M. Rizkinia, R. Nur Hidayati, and F. Yugi Hermawan, "Real-time stress detection and monitoring system using IoT-based physiological signals," *Bulletin of Electrical Engineering and Informatics*, vol. 12, no. 5, pp. 2807–2815, Oct. 2023, doi: 10.11591/eei.v12i5.5132.

[20] M. Priya D, H. Haran S, B. Rohith, Hariprasath M, and J. Kumar P, "Detection of stress by machine learning in IT industry," in *2023 7th International Conference on Computing Methodologies and Communication (ICCMC)*, Feb. 2023, pp. 53–56, doi: 10.1109/ICCMC56507.2023.10083884.

[21] U. S. Reddy, A. V. Thota, and A. Dharun, "Machine learning techniques for stress prediction in working employees," in *2018 IEEE International Conference on Computational Intelligence and Computing Research (ICCIC)*, Dec. 2018, pp. 1–4, doi: 10.1109/ICCIC.2018.8782395.

[22] T. R. P. H. S. R., D. D. M. D. M., N. M. D. S., P. A. D. Thameera, W. A. C. Pabasara, and H. A. Caldera, "Workload management system for IT professionals through stress identification," *International Research Journal of Innovations in Engineering and Technology*, vol. 7, no. 10, pp. 326–332, 2023.

[23] A. Hinze, J. Bowen, and J. L. König, "Wearable technology for hazardous remote environments: smart shirt and rugged IoT network for forestry worker health," *Smart Health*, vol. 23, Mar. 2022, doi: 10.1016/j.smhl.2021.100225.

[24] Suhas KS and Phaneendra HD, "Stress prediction in working employees using artificial intelligence of things," *Journal of Pharmaceutical Negative Results*, vol. 13, no. 1, Jan. 2022, doi: 10.47750/pnr.2022.13.S01.237.

[25] R. Sharma, S. Rani, and D. Gupta, "Stress detection using machine learning classifiers in internet of Things environment," *Journal of Computational and Theoretical Nanoscience*, vol. 16, no. 10, pp. 4214–4219, Oct. 2019, doi: 10.1166/jctn.2019.8502.

[26] L. Malviya *et al.*, "Mental stress level detection using LSTM for WESAD dataset," in *Proceedings of Data Analytics and Management: ICDAM 2022*, 2023, pp. 243–250, doi: 10.1007/978-981-19-7615-5_22.

[27] A. Mustafa, M. Alahmed, A. Alhammadi, and B. Soudan, "Stress detector system using IoT and artificial intelligence," in *2020 Advances in Science and Engineering Technology International Conferences (ASET)*, Feb. 2020, pp. 1–6, doi: 10.1109/ASET48392.2020.9118345.

[28] S. Gedam and S. Paul, "Automatic stress detection using wearable sensors and machine learning: a review," in *2020 11th International Conference on Computing, Communication and Networking Technologies (ICCCNT)*, Jul. 2020, pp. 1–7, doi: 10.1109/ICCCNT49239.2020.9225692.

[29] R. Krishna Vanakamamidi, L. Ramalingam, N. Abirami, S. Priyanka, C. S. Kumar, and S. Murugan, "IoT security based on machine learning," in *2023 Second International Conference on Smart Technologies For Smart Nation (SmartTechCon)*, Aug.

2023, pp. 683–687, doi: 10.1109/SmartTechCon57526.2023.10391727.

[30] T. R. Saravanan, A. R. Rathinam, J. Lenin, A. Komathi, B. Bharathi, and S. Murugan, "Revolutionizing cloud computing: evaluating the influence of blockchain and consensus algorithms," in *2023 3rd International Conference on Smart Generation Computing, Communication and Networking (SMART GENCON)*, Dec. 2023, pp. 1–6, doi: 10.1109/SMARTGENCON60755.2023.10442008.

[31] C. C. Sekhar, V. V, K. Vijayalakshmi, M. B. Sahaai, A. S. Rao, and S. Murugan, "Cloud-based water tank management and control system," in *2023 Second International Conference on Smart Technologies for Smart Nation (SmartTechCon)*, Aug. 2023, pp. 641–646, doi: 10.1109/SmartTechCon57526.2023.10391730.

[32] K. Karthika, S. Dhanalakshmi, S. M. Murthy, N. Mishra, S. Sasikala, and S. Murugan, "Raspberry Pi-enabled wearable sensors for personal health tracking and analysis," in *2023 International Conference on Self Sustainable Artificial Intelligence Systems (ICSSAS)*, Oct. 2023, pp. 1254–1259, doi: 10.1109/ICSSAS57918.2023.10331909.

[33] S. Selvarasu, K. Bashkaran, K. Radhika, S. Valarmathy, and S. Murugan, "IoT-enabled medication safety: real-time temperature and storage monitoring for enhanced medication quality in hospitals," *2nd International Conference on Automation, Computing and Renewable Systems, ICACRS 2023 - Proceedings*, pp. 256–261, 2023, doi: 10.1109/ICACRS58579.2023.10405212.

BIOGRAPHIES OF AUTHORS

Muthukathan Rajendran Sudha received the Ph.D. degree in computer science from University of Madras in 2022. She received the master's degree in computer science from Madurai Kamarj University, Madurai, Tamil Nadu, India in 1996. Since 2012, she has been working as an assistant professor in the Department of Computer Applications at the SRM Institute of Science and Technology (formerly known as SRM University) in Chennai, India. Her research focuses on internet of things (IoT), green energy in cloud data centers, cloud and mobile cloud computing, and artificial intelligence (AI) and machine learning. She is having 23 years teaching experience in the department of computer science. She has been working as lecturer cum head of the Department of Computer Science in N. M. S. Sermathai Vasan College for women, Madurai, India. She is a lifetime member of the international association of engineers (IAENG) since 2018. She has published 16 articles in peer reviewed international journals and presented 12 papers in international conferences. She can be contacted at email: sudham2@srmist.edu.in.

Gnanamuthu Bai Hema Malini received the Ph.D. degree in computer science from University of Madras in 2023. She received the master's degree in computer applications from Manomanaiam Sundaranar University, Tirunelveli, Tamil Nadu, India in 2002. Since 2009, she has been working as an assistant professor in the department of computer applications at the Shrimathi Devkunvar Nanalal Bhatt Vaishnav College for women in Chennai, India. Her research focuses on image processing and machine learning. She is having 17 years teaching experience in the Department of Computer Science. She has published 4 articles in peer reviewed international journals and presented 3 papers in international conferences. She can be contacted at email: gbhmalini@yahoo.co.in.

Rangasamy Sankar received B.E. degree in electrical and electronics engineering from Government College of Engineering, Tirunelveli and M.E. degree in control and instrumentation from Anna University, CEG, Chennai in 1995 and 2001 respectively. He received the Ph.D. degree in electrical engineering from Sathyabama Institute of Science and Technology, Chennai in 2012. He has 24 years of work experience in the field of teaching from various reputed academic organizations across Tamil Nadu, India, since the year of 1996. He has also published his research papers in various reputed Scopus and SCI journals. He is currently working as professor in Chennai Institute of Technology, Chennai. His research area is power electronics and drives. He is the life member of Indian society for technical education, and other professional societies. He can be contacted at: sankar3673@yahoo.com.

Murugaaboopathy Mythily holds a doctorate from Anna University, with bachelor's and master's degrees specializing in computer science and engineering from Avinashilingam Deemed University and Government College of Technology, Coimbatore, Tamil Nadu, India, respectively. Currently, she serves as an associate professor at Karunya Institute of Technology and Sciences. With two decades of experience spanning both industry and academia, her expertise encompasses software engineering, design patterns, problem-solving techniques, and data science. Dr. Mythily has contributed significantly to her field with over 30 publications in refereed international journals and conference proceedings. She can be contacted at email: mythily.m@gmail.com.

Piskala Sathiyamurthy Kumaresh working as an associate professor in the Department of Electronics and Communication Engineering at K.L.N. college of engineering, Pottapalayam, Sivagangai District Pin-636012. He is having rich experience in teaching more than 19 years in reputed institutions. He is an awesome researcher too in the field of communication, networks. To his credit, he has published many research articles in well reputed journals also. He can be contacted at email: kumaresh.ps@klnce.edu.

Mageshkumar Naarayanasamy Varadarajan is an industry leader and distinguished engineer with over 22 years of experience, captivated the audience with his insights into software development, testing, and DevOps. Well versed with multiple languages, solving critical issues, and leading teams, he spearheaded architectural changes for large scale projects, modernized legacy systems to enhance efficiency and performance, and defined cloud-agnostic solutions, all while receiving recognition for innovative solutions and various successful project implementations. Mageshkumar demonstrates outstanding knowledge in a variety of expertise including cloud and data security, and new technologies like AI and machine learning. He can be contacted at email: magesh27@gmail.com.

Shanmugam Sujatha is an adjunct professor, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Chennai, Tamil Nadu, India. She published her research articles in many international and national conferences and journals. Her research areas include network security and machine learning. She can be contacted at email: sujathasmvr@gmail.com.