IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 17 July 2024, accepted 14 August 2024, date of publication 21 August 2024, date of current version 30 August 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3446875

RESEARCH ARTICLE

Real Time Worker Stress Prediction in a Smart Factory Assembly Line

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ABSTRACT This research contributes to a innovative approach to address the increasing issues of workplace mental health and stress, particularly in high-pressure environments like assembly lines which also affects workers performance and companies productivity. Recognizing the harmful effects of stress on worker productivity, this study introduce stress-monitoring model using advanced machine learning techniques. Proposed model integrates Internet of Things (IoT) technology and machine learning techniques, utilizing a wearable watch to gather open-source physiological data indicative of workers stress in assembly lines. Key physiological markers, such as heart rate, respiration rate, and skin conductance, are analyzed. Based on these physiological indicators, the primary objective is to develop and validate framework that can accurately predict worker stress levels using IoT and machine learning models. The empirical results of the proposed approach demonstrate that the most effective model achieves an impressive accuracy score, with the XGBoost model providing 99% accuracy and Matthew's correlation coefficient (MCC) of 0.99, surpassing the performance of Logistic Regression (LR), Decision Tree (DT), Random Forest (RF), k-Nearest Neighbors (kNN), and Support Vector Machine (SVM). The practical implications of these findings suggest a significant potential for implementing such technology in high-stress work settings, offering a proactive tool for stress management and contributing to enhanced worker well-being and productivity.

INDEX TERMS Workplace safety, smart factory, assembly line, real time stress prediction, worker's safety, production optimization.

I. INTRODUCTION

In recent years, the advent of smart factories has marked the onset of a new era in manufacturing. This era has been characterized by the integration of cutting-edge technologies, such as the Internet of Things (IoT), Big data analytics, and Artificial Intelligence (AI). These technological advancements have been instrumental in optimizing production processes, enhancing efficiency, and boosting productivity [1]. However, the rapid increase of smart factories has raised concerns regarding workers' well-being in these high-tech environments [2]. According to [3] workplace stress has far-reaching consequences, including reduced job satisfaction, increased absenteeism, and decreased productivity. The introduction of advanced automation and continuous monitoring of worker performance in smart factories has worsened these concerns. To address these challenges, researchers are increasingly exploring predictive analytics within the context of smart factories to identify and mitigate sources of worker stress [4]. Predictive analytics leverages machine learning algorithms and predictive modeling techniques to analyze real time data and detect patterns [5]. This approach aims to

The associate editor coordinating the review of this manuscript and approving it for publication was Huaqing Li.

proactively identify factors contributing to workplace stress, enabling early intervention and prevention strategies [6].

In addition, wearable smart devices have emerged in recent years as a promising solution for alleviating workplace stress [7]. These wearable devices, including smartwatches and fitness trackers, can monitor workers' physiological responses to their work environment, offering valuable insights into potential stressors. For instance, they can track heart rate, body temperature, and other biometric data in real time, helping identify stress-inducing conditions such as high-temperature environments or physically demanding tasks [3]. Furthermore, wearable devices provide critical insights into human factors within the workplace [8]. Human factors encompass the interactions among individuals, machines, and the work environment, significantly influencing worker performance and well-being. Researchers are exploring human-machine collaboration to optimize assembly lines by harnessing the strengths of both human and machine workers [8]. Wearable smart devices can also monitor worker movements, posture, and physical activity, thereby detecting potential ergonomic hazards that may lead to musculoskeletal disorders (MSDs) or other injuries [2]. The advantage of wearable devices lies in their non-invasive and automated nature, allowing for continuous data collection without disrupting workflow [9]. By embracing wearable devices and advanced technologies, smart factories have the potential to proactively identify and address sources of worker stress and ergonomic risks, creating safer and more sustainable work environments. These technologies empower workers to monitor and manage their health, well-being, and performance in real time.

Additionally, wearable devices contribute to optimizing manufacturing processes by identifying inefficiencies and bottlenecks, thereby enhancing productivity and reducing the risk of errors or accidents in the workplace. This paper investigates the relationship between stress, worker well-being, and productivity within the context of smart factories. Specifically, it explores the role of wearable devices and human factors in mitigating workplace stress. By conducting a comprehensive review of existing research and case studies, this study sheds light on the potential benefits and challenges associated with assembly line workers using wearable smart devices. What sets our study apart is its comprehensive and interdisciplinary approach to addressing workplace stress in smart factories. While previous research has touched upon aspects of automation and worker well-being [2], our study integrates predictive analytics, wearable devices, and human factors optimization in a novel stress monitoring and management framework. This innovative approach represents a significant leap toward addressing the complex challenge of worker stress in the context of smart manufacturing.

The remainder of this article is structured as follows: Section II discusses the latest trends in smart factories, advancements in worker stress prediction, and the increasing automation facilitated by wearable devices in the workplace. Section III presents the proposed methodology and framework development, including details about the dataset and model training. The detailed results are thoroughly discussed in Section IV. Section V highlights the findings, situating them within the existing literature and considering potential implications for industry practice. Finally, Section VI concludes this research, key takeaways, and prospects for future research.

II. LITERATURE REVIEW

This section explores how technologies are transforming industrial workplace environments and future assembly lines. The smart factories section explores how concepts and technologies like IoT, big data analytics, cloud services, and digital twins are transforming traditional factories into factories of the future. Finally, the section ends by addressing the need for the proposed system and how it can be achieved.

A. SMART FACTORIES

As mentioned, smart factories are manufacturing facilities that leverage advanced technologies like IoT, big data analytics, artificial intelligence, and automation to optimize production processes. These facilities use interconnected sensors, devices, and machines to generate large amounts of real time data [10]. The data are then analyzed to identify patterns, optimize processes, and improve product quality. Figure 1 shows smart factories depend on different technologies working harmoniously to optimize processes, production, and maintenance.

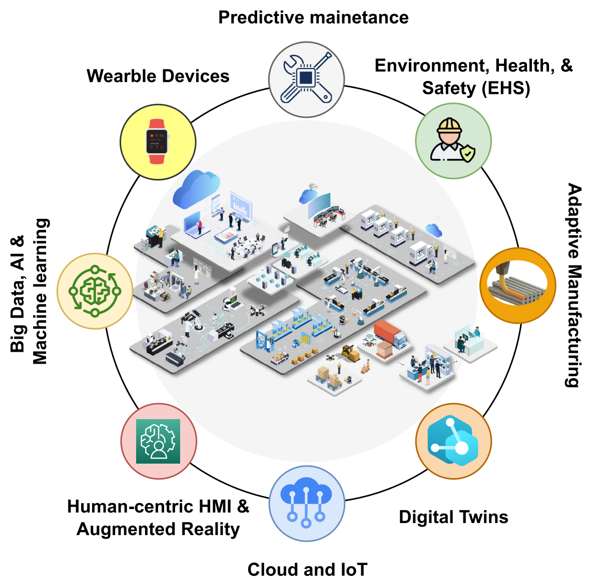


FIGURE 1. I4.0 technologies in a smart factory environment.

The IoT is a network comprising physical objects, devices, and sensors capable of exchanging data. IoT devices have sensors that monitor machine performance, robots that assist with assembly, and Radio Frequency Identification (RFID) tags that track the movement of materials and products. These data can be used for Prognostics and

Health Management (PHM) to monitor equipment health and prevent failures. According to a study by Sarkar et al., with the introduction of big data technologies, massive amounts of structured and unstructured data are produced by various sources [11]. More precisely, smart factories generate vast amounts of data that can be analyzed to identify trends and optimize inventories and supply chain operations. Clausen and Li presented statistical and computational methods to extract insights from collected data [12]. In smart factories, data analytics can identify patterns and needs to perform predictive maintenance.

Artificial intelligence (AI) is the term used to describe computer systems that can execute tasks that typically necessitate human intelligence, such as problem-solving, learning, and decision-making. AI can automate processes, optimize production, and improve quality control in smart factories. For example, AI-powered robots can perform complex tasks with high precision and consistency, reducing the risk of human error. A case study applied by Leberruyer et al. at a manufacturing facility in Sweden assessed the effectiveness of using AI to support a defect detection strategy for their products [13]. Innovative technologies such as digital twins can help replicate a physical process in a virtual environment. This approach can help reduce the risk of errors or inefficiencies in the real-world production process and optimize the factory's overall performance. In a recent study by Friederich et al., the authors proposed a digital twin-based production scheduling system for smart factories. The system used a digital twin to simulate and optimize production processes, allowing for more efficient and effective scheduling of the resources [14]. The smart factory can achieve operational excellence by integrating digital twins with the human-machine interface (HMI) framework. The digital twin visually represents the physical processes, enabling accurate replication and analysis. Moreover, the HMI framework enables operators to interact with the digital twin, facilitating real time monitoring, control, and optimization of the production schedule and resource allocation. However, limitations of HMI-based study included incomplete real-world implementation and evaluation, reliance on limited and imbalanced datasets, and issues with misclassifying approved product classes. This research also highlighted the model's limited capability in detecting new defect types, suggesting the need to expand its application to various products and enhance system calibration. [15]

Bagassi et al. proposed a human-machine interaction framework for an intelligent airport control tower based on Augmented Reality (AR). Using these intuitive and user-friendly interfaces, operators can interact with complex systems and understand the insights data analysis tools provide [16]. However, deployment on a local web server offers a potential solution. The literature evaluating AR interfaces for airport control towers reveals the early development stage of AR technology for spatial display solutions and the insufficient maturity of head-mounted AR display technology for safety-critical environments. This highlights the need for further research in real-world settings and extensive user acceptance testing to ensure effective integration and usability. These limitations collectively highlight the evolving nature of technological advancements in these areas, emphasizing the need for continuous research and development, robust and scalable system designs, and user-centric approaches in technical applications.

Zakeri et al. presented cognitive and multimodal approaches using subjective and behavioral measurement in smart factories. The study used electroencephalography (EEG) and functional near-infrared spectroscopy (fNIRS) signals to investigate worker's mental health in a factory. However, that approach has limitations owing to some participant data was excluded because of low quality, potentially influencing the study's conclusions. The lack of detailed information on participants' technical expertise might affect the results' broader relevance. The study's stringent criteria, such as age and motor capabilities, may limit its applicability. Moreover, by concentrating on a particular task, the research might not cover all possible scenarios of human-robot cooperation in industrial environments [17]. On the other hand, Soori et al. composed a review of the smart factories. According to the review, smart factories face several critical challenges as they integrate a growing number of Internet-connected devices, with security and privacy of data being paramount. The continuous power requirement for IoT devices poses a challenge to energy efficiency, impacting costs and consumption in environments where power may be limited or costly. Additionally, the need for seamless integration with supply chain, logistics, and customer relationship management systems is crucial, and any lack thereof can compromise efficiency and effectiveness. Interoperability issues among IoT devices from different vendors further complicate the seamless integration and management of these devices, requiring specialized expertise and significant resources. These challenges underscore the necessity for ongoing research and development to overcome the obstacles faced by smart factories [18].

This study aims to address the gaps identified in previous studies by implementing real time stress prediction framework for workers using wearable smart devices and machine learning to improve their well-being and operational efficiency in a smart factory environment. Moreover, it is required to analyze stress-related data and patterns using advanced algorithms and offer personalized recommendations and insights to prioritize the health, productivity, and operational efficiency of the workforce.

B. WORKER'S STRESS PREDICTION IN ASSEMBLY LINE

Regardless of increased automation in Industry 4.0, manual and semi-automated processes still exist. Assembling products on a manual or semi-automatic assembly line is a stressful task. The literature illustrates the physical and mental stress inherent of manual assembly tasks. Intelligent systems based on machine learning can be developed to predict the likelihood of stress and burnout among workers on assembly lines. In their study, Tropschuh et al. presented a methodology for measuring the physical and mental strain workers experience while performing manual assembly tasks [19]. To evaluate the levels of physical and psychological strain encountered by laborers, the authors proposed a method involving physiological measurements (such as heart rate variability, skin conductance, and electromyography), self-reported measures, and observational data. However, potential limitations included the small sample size of test participants, the use of a laboratory environment rather than a real-world manufacturing setting, and the lack of diversity in the test participant pool (all participants were fit and able to work). Additionally, the study only focused on one specific assembly task and did not consider other types of manual assembly work. A study by Falahati et al. employed a fuzzy logic approach to forecasting the likelihood of work-related musculoskeletal disorders (WMSDs) among automobile assembly workers [20]. The authors recognized that WMSDs were a prevalent problem among assembly line workers, and effective prevention strategies were necessary to minimize their occurrence. The authors found that the developed fuzzy logic model had a high level of accuracy in predicting the risk of WMSDs among automotive assembly workers. The most significant risk factors for WMSDs identified in the study were working in a standing position for a long time, performing repetitive tasks, and working in awkward postures. Nevertheless, the study had some limitations, such as sample size, demographic factors, self-reported measures, limited risk factors, and external validity.

According to recent studies, Dogan and Birant gave a review of machine learning methods and manufacturing challenges during the fourth industrial evolution [21]. However, the this review lacked in precisely specifying applications for the real-time stress prediction platforms. Sedighi et al., discussed three types of learning-based models to formulate the worker's stress behavior using limited data. Those are statistical models, classifiers, and ensemble models [22]. However the research didn't develop the real-time stress prediction system using the wearable devices. Pabolu et al. proposed machine learning techniques to forecast the time that assembly line workers could work comfortably but did not provide any comprehensive real-time monitoring solution [23]. The study collected data using wearable sensors to collect physiological data. The collected data were used to develop a machine learning model to predict the worker's optimal work-duration time. Similarly, Ramirez et al. developed a method for predicting standard times in assembly lines using least squares in multivariate linear models [24]. The study was conducted in a manufacturing company in Ecuador to predict the standard times of an assembly line of industrial motors. The researchers concluded that the developed method could be a practical tool for predicting standard times in assembly lines, which could help optimize the production process, reduce costs, and improve the company's competitiveness. However, this research focused more on productivity optimization rather than workers stress prediction and well-being.

A recent study by Iqbal et al. introduced an approach to detect and classify stress levels [25]. The authors proposed an automatic feature selection method that utilized genetic algorithms and SVM. The aim was to identify relevant features contributing to accurate stress classification by analyzing heart and respiratory rate signals. While the study did not provide specific accuracy figures, it acknowledged that the model's accuracy in the study was low and the system lacked real-time capabilities. Nonetheless, it highlighted the improved performance of the automatic feature selection method compared to manual feature selection techniques. Battini et al. provided human oriented assembly line balancing and sequencing study. The researchers emphasized workers' comfort zone in terms of ergonomic insight using the dataset collected through smartwatches. Nevertheless, the study had drawbacks in terms of specific ergonomic conditions. The model's applicability might be limited to specific types of assembly lines and may not extend to more diverse manufacturing environments [26].

The literature focuses predominantly on manual and semi-automated assembly lines, leaving a notable gap in applying stress prediction techniques to fully automated assembly processes. Additionally, many studies tend to narrow their scope by concentrating on specific industries or regions, limiting the generalizability of their findings. Moreover, there is a need for more accurate stress prediction models, as indicated by some studies reporting low accuracy rates. This section also highlights the underexplored potential of wearable technology for stress prediction in assembly lines, pointing to a research gap in fully harnessing wearable sensors. Furthermore, long-term comfort and usability concerns associated with wearing such devices throughout the workday remain insufficiently addressed. The literature primarily focuses on physiological measurements, missing the opportunity for interdisciplinary approaches that integrate various workplace factors. The preventive measures to reduce stress among assembly line workers are also an underexplored area. Lastly, there is a research gap in assessing the generalizability of stress prediction methods to diverse industries and contexts, along with a need to investigate the feasibility of long-term stress monitoring and intervention strategies. Addressing these research gaps presents significant opportunities for advancing the field and enhancing worker well-being in assembly line environments.

C. WEARABLE DEVICES AND AUTOMATION IN WORKPLACE

Wearable devices and automation are revolutionizing the workplace by improving productivity and safety. Wearable devices provide real time data and insights while automation streamlines repetitive tasks. This integration reshapes the workplace, empowering organizations to achieve greater efficiency and worker well-being. A study by Han et al.

investigated the feasibility of using wearable devices to detect work-related stress among office workers [3]. Physiological data from 20 office workers in China was collected and used to train a machine learning model to predict the worker's stress levels. Results demonstrated that wearable devices can be a practical tool for detecting work-related stress among workers. The authors suggested that the developed system could be integrated with other workplace interventions to prevent and manage work-related stress. The findings of this study can help promote workplace safety and health, thus improving working conditions to address high-pressure environments like assembly lines. Fardhosseini et al. used a three-axis accelerometer to recognize the physical fatigue of construction workers [27]. Bottani et al. aimed to create and evaluate two interactive mixed reality (MR) solutions that could be used as a wearable smart device [2]. The study focused on using these solutions to diagnose faults and provide aid within manufacturing systems, particularly within an aseptic bottling production line. Webel et al. proposed an augmented reality (AR) based training platform to enhance the assembling and maintenance skills of the workers [28]. The objective was to facilitate skill acquisition more efficiently and engagingly.

Han et al. developed a wearable device to detect work related stress by measuring physiological signals and activity data [3]. The device detected work-related stress and suggested it could be a valuable tool for monitoring and managing work-related stress. The study by Rodrigues and Marchetti highlighted the potential of wearable technology to improve occupational health and safety. It suggested that further research is needed to develop more sophisticated and accurate devices. In conclusion, it was evident that existing studies in the literature primarily revolve around offline prediction systems or focused on specific case studies. Rodrigues and Marchetti proposed a stress detection framework based on a deep learning method that used face images obtained from video only [29]. It was a non-invasive approach to stress detection and detects a worker's effective state as non-stressed or stressed depending on facial images. However, this approach had its own limitations of handling image data and scalability. Arpaia et al. proposed a wearable single-channel instrument made of dry electrodes and simple components that detects human stress in real time via electroencephalography (EEG) [30]. The objective of the single-channel differential measurement is to analyze the frontal asymmetry. Thus, the instrument was characterized metrologically on human subjects, where psychologists gave out triple references, standardized tests, observational questionnaires, and performance measurements. SVM, k-NN, random forest, and ANN machine learning classifiers were trained on 50% of the dataset and used to classify the rest of the data.

Morshed et al. aimed to comprehend and gauge workplace stress experienced by remote information workers [31]. They employed passive sensors and behavioral data from 46 such workers. The data collection involved pervasive sensors like keyboards, webcams, and passive behavioral data, including email communication and calendar schedules. Moreover, experience sampling was applied in collecting ground truth self-reported measures of stress. Machine learning was used to analyze the data collected by treating the problem as a binary classification with low levels. The samples were separated using the adaptive baseline approach, while the predictive performance of different classifiers was utilized for stress prediction. Rescio et al. presented a worker's stress detection platform through a wearable and environmental system [32]. The device was minimally invasive, incorporated a camera, and analyzed heart rate, galvanic skin response, and camera RGB signals. The software incorporated in the device was validated using a supervised method. However, the proposed approach lacked long-term usability. Shishavan et al. evaluated the influence of stress originating from work and incidents of workplace violence by analyzing continuous physiological signals [33]. The study developed a multiparameter wearable armband to monitor the physiological state of workers. Various worker populations were monitored where stress responses were connected with pulse transit time (PTT) alterations and heart rate variability (HRV). As per the results, the HRV decreased on workdays compared to non-workdays. Simultaneously, the pulse transit time PTT consistently declined, indicating heightened blood pressure.

Leone et al. recommended a framework that analyzed heart rate, galvanic skin response, and electrooculogram signals to obtain that can detect excessive stress or cognitive load by using two wearable devices: Empatica E4 wristband and J!NS MEME electrooculography glasses [34]. The approach was tested in the laboratory, focusing on the LEGO brick-based simulation of manufacturing devices, limiting its real-world applicability. Umer examined the feasibility of simultaneously monitoring physical and mental stress by employing machine learning algorithms and physiological measurements [35]. The data was collected using an Equivital EQ02 Life monitor vest to detect physiological parameters. The vest had electrocardiography (ECG), skin temperature, breathing, and skin conductance sensors. The sliding window approach was used for machine learning. Maeda et al. proposed an unconscious stress monitoring system for office workers called COSMOS [36]. According to the study, COSMOS is a system that continuously and unconsciously acquires physiological information through ordinary laptop or computer components like a camera or mouse. COSMOS then collected crucial information such as eye gazing, facial expression, mouse movement, heart rate, etc. However, this research focuses on office workers rather than high-stress assembly line environments.

The studies discussed within this section have limited diversity in their choice of study participants, focusing on specific worker groups or regions. This narrow scope may hinder the generalizability of their findings to a broader spectrum of industries and workplace contexts. Secondly, while some studies report high accuracy in stress detection using wearable devices, others lack specific accuracy figures, leading to a lack of standardized metrics for performance evaluation. This discrepancy makes it challenging to compare the effectiveness of different wearable devices objectively. Thirdly, there is a gap in understanding the long-term comfort and usability of these devices, which is crucial for worker acceptance and sustained use. Additionally, the predominant focus on physiological measurements neglects interdisciplinary approaches that could provide a more comprehensive understanding of workplace stress. Furthermore, limited research has been conducted on proactive and preventive measures to mitigate stress among workers. The research also lacks exploration into the adaptability of stress prediction methods and wearable devices to diverse industries and workplace contexts. Lastly, the feasibility of continuous, long-term stress monitoring and intervention strategies remains under-explored. Addressing these limitations is imperative to advance our knowledge on the role of wearable devices and automation in addressing workplace stress and enhancing worker wellbeing.

III. PROPOSED METHODOLOGY

This study proposes an innovative framework for stress monitoring using IoT and machine learning for workers in a high-stress assembly line work environment. To develop the proof of concept, we used an open-source dataset collected through a wearable watch to monitor physiological signals associated with stress, such as heart rate, respiration rate, and skin conductance [37]. We used the data to develop machine learning models to predict stress levels based on these physiological signals. We also proposed an architecture to perform real time monitoring of worker's stress levels in a smart factory environment. Based on the insights generated by the model, a Graphical User Interface (GUI) is proposed to deploy the best models in the production environment. If deployed and used effectively, we believe the proposed systems can help improve productivity, reduce bottlenecks, and benefit worker's health and well being.

More precisely, the objective is to predict stress levels in real time using physiological data gathered from the Empatica E4 wearable watch. These data include heart rate, respiratory rate, skin conductance, and stress labels from 35 volunteers. Our approach involved preprocessing this data to remove outliers and standardize formats, training machine learning models like Logistic Regression, Decision Tree, and Random Forest, and optimizing these models through hyperparameter tuning. Evaluation metrics include accuracy, Matthew's correlation coefficient, precision, recall, and F1 score. Finally, the study proposes a real time monitoring architecture and a GUI for practical application in a production environment. This ensures a comprehensive approach to address real time stress monitoring challenges in smart factory settings. The development of the proposed system involves three main steps: data preparation, model training, and model deployment in the production environment for real time worker's stress prediction. The following sections describe these steps in further detail.

A. REAL TIME WORKER'S STRESS PREDICTION FRAMEWORK

This section explains how the proposed system can generate real time insights from raw data in a production environment. Real time data collection and transmission in the workplace for worker mentoring using IoT involves various interconnected devices. This step could be done using wired or wireless communication protocols such as Wi-Fi or Bluetooth [38]. To achieve real time stress prediction, workers at each station would wear a wireless smart watch while engaged in work on the assembly line. This watch is the exact watch used to initially collect the data for model training (Empatica E4). Figure 2 serves as a conceptual illustration of the proposed end-to-end framework, showcasing the entire process from raw data to insight generation. Specifically, it depicts the functionality of the watch's wireless connectivity feature, which enables the real time transmission of worker's statistics to a central storage system. Notably, this central storage system has the flexibility to be hosted on either edge devices or cloud-based platforms [39]. Once the data are collected and transmitted to a central system for storage, they can be loaded, preprocessed (removing any noise, outliers, or missing values), and transformed to feature vectors. The deployed model can be used for real time decision-making from the input feature vector.

TABLE 1. Attributes in dataset.

Attribute	Data type
Participant id	Integer
Heart rate (HR)	Float
Respiratory rate (RR)	Float
Time	Timestamp
Label	Binary

B. DATASET

We utilized an open-source stress monitoring dataset originally proposed in [37] for proof of concept. The target dataset comprises 5 columns, including participant identification, heart rate (HR), respiratory rate (RR), time on which each reading was recorded, and label columns stating if the participant was stressed or not at the time of reading. Table 1 lists various attributes of the data along their type. The wearable device used to collect data was Empatica E4, which is a medical-grade watch classified as a Class IIA Medical Device under the 93/42/EEC Directive. The Empatica E4 can efficiently monitor physiological changes based on the photoplethysmogram (PPG) signal. The watch also has wireless connectivity, real time data streaming, and onboard storage.

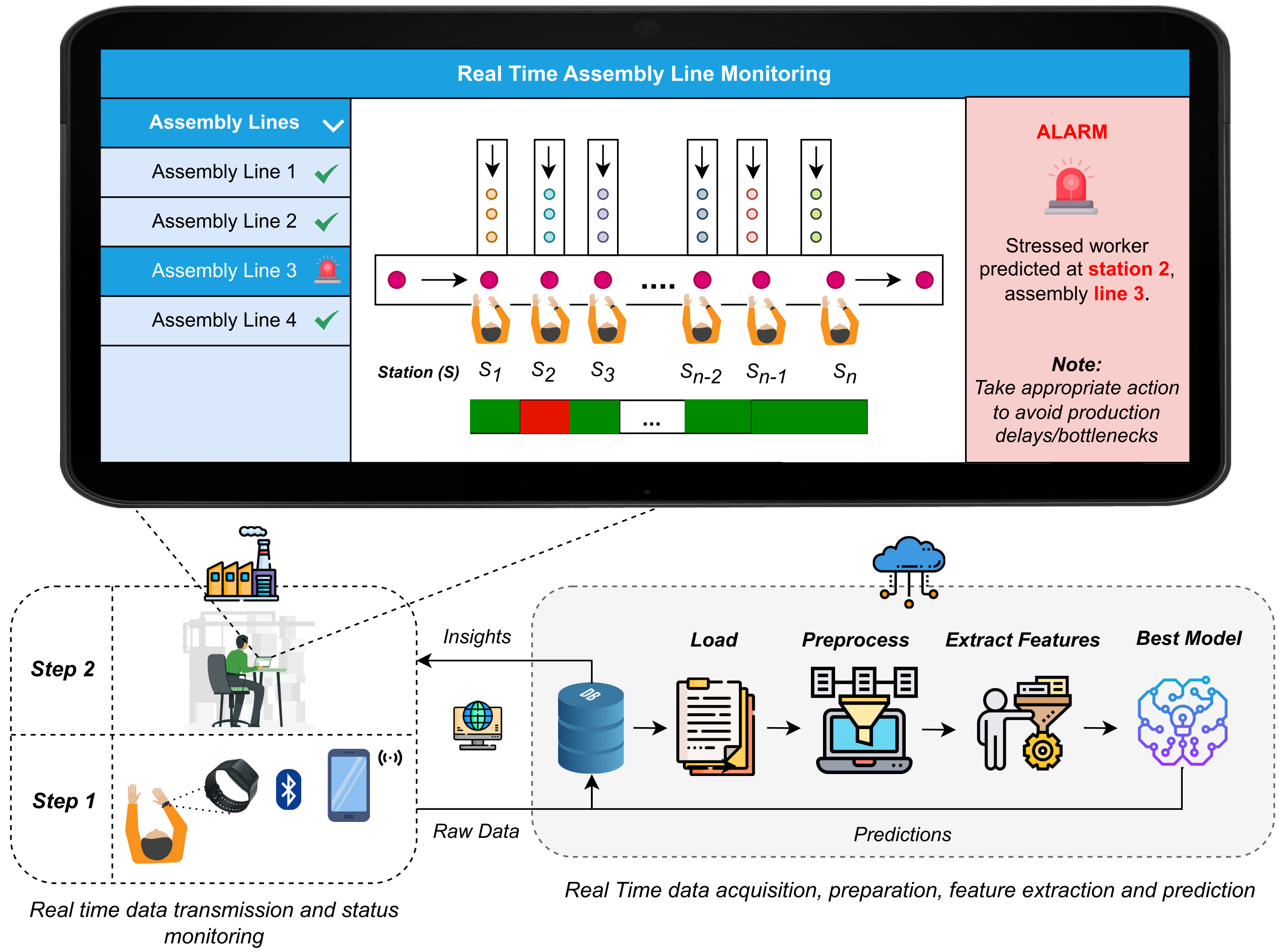
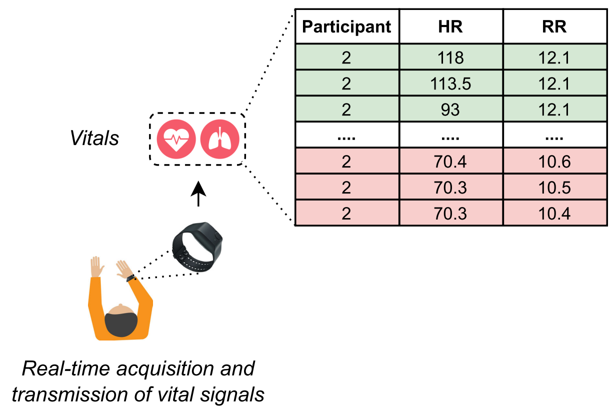


FIGURE 2. Real time worker's stress prediction framework.

To collect data, volunteers were asked to perform three stress-inducing tasks (interview session, Stroop color-word test, and hyperventilation period) with a standard baseline period. For each participant, tests took 60 minutes on average. The collection method is completely non-invasive, using the smartwatch mentioned above. The participant's age ranges between 18 and 75 years, which shows diverse participation and applicability to people from various age groups. The dataset comprises 112,516 samples, averaging 3308 data samples per participant. The open-source dataset is already preprocessed and has no outliers. Further details about the dataset can be found in the respective pilot study [37]. Figure 3 shows samples from the dataset for participant 2 in normal and stressed states.



Participant	HR	RR
2	118	12.1
2	113.5	12.1
2	93	12.1
....	....	....
2	70.4	10.6
2	70.3	10.5
2	70.3	10.4

FIGURE 3. Data sample for participant 2 in normal and stressed states.

C. MODEL TRAINING

This section describes how to train a machine learning model to automatically classify whether the participant is stressed or not. Multiple models were trained to identify the best modeling technique for the task. After preprocessing and feature extraction, the data was divided into training and test sets. Out of the total 112,516 samples, about 70% (78,761) samples were used for model training, and 30% (33,755) samples were used for testing model performance. Indeed, in machine learning, hyperparameters are those that are not learned during training but are set before training

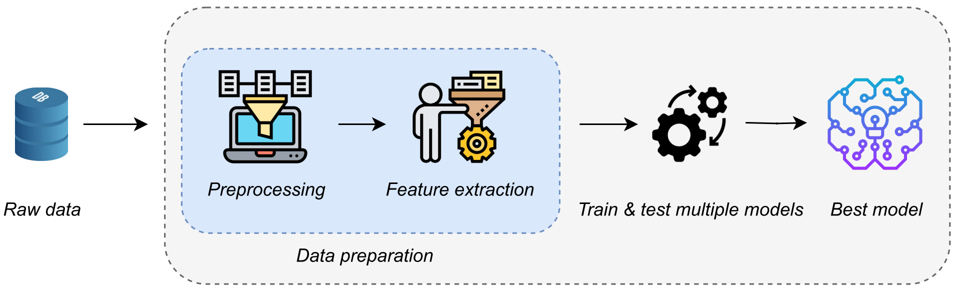


FIGURE 4. Training pipeline of the machine learning model (from raw data to the best model).

TABLE 2. Hyperparameters and search space of grid search.

Classifiers	Parameters and Search Space
Logistic Regression	$penalty : [l1, l2]$
	$C : [1.0, 0.5, 0.1]$
	$solver : liblinear$
Decision Tree	$criterion : [gini, entropy]$
	$min\_samples\_leaf : [1, 2, 3, 4, 5, 6]$
	$max\_depth : [1, 2, 3, 4, 5, 6]$
	$min\_samples\_split : [2, 3, 4, 5, 6]$
Random Forest	$min\_samples\_leaf : [1, 2, 3, 4, 5, 6]$
	$max\_depth : [1, 2, 3, 4, 5, 6]$
	$min\_samples\_split : [2, 3, 4, 5, 6]$
K-Nearest Neighbors	$n\_neighbors : [1, 2, 3, 4, 5, 6]$
	$weights : [uniform, distance]$
	$metric : [euclidean, manhattan]$
Support Vector Machine	$Kernel : [linear, rbf]$
	$C : [1, 2, 3, 4, 5, 6]$
XGBoost	$learning\_rate : [.1, .2, .3]$
	$max\_depth : [1, 2, 3, 4, 5, 6]$
	$min\_child\_weight : [1, 2, 3]$
	$subsample : [1.0, 0.5, 0.1]$
	$n\_estimators : [50, 100, 150]$

begins. These hyperparameters can significantly impact the model's performance, and choosing the correct values for them is often critical for achieving good results [40]. Grid search is a common method for hyperparameter tuning. It involves creating a grid of possible values for each hyperparameter and evaluating the model's performance using possible combinations of hyperparameters in the given range. Table 2 lists different classification models tested during training. It also lists the hyperparameters being tuned for each classifier.

As shown in table 2 we performed training using various classification algorithms to identify a suitable model for the task. Figure 4 shows the model training pipeline from raw data to the best model. As mentioned in section III-A, the data used for model training were already preprocessed, but we included these steps in the training pipeline. In case the model deployment in the production environment, the new raw data values will also need to be preprocessed before input to the classification model.

D. EVALUATION METRICS

The best model was selected based on various statistics, including accuracy, Matthew's correlation coefficient (MCC), precision, recall, F1 score, and confusion matrix. In brief, the accuracy score represents the proportion of correctly classified instances out of all tested instances. Equation 1 shows the formula of accuracy, where TP = True Positives, TN = True Negatives, FP = False Positives, and FN = False Negatives.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

Although accuracy is commonly used to measure classification performance, accuracy is asymmetrical and can be affected by class imbalance problems. In contrast, the MCC score is a more reliable metric for evaluating classification performance. Equation 2 shows the formula to calculate the MCC score.

$$MCC = \frac{(TP \times TN) - (FP \times FN)}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \tag{2}$$

MCC score ranges between −1 and 1, where an MCC score of 1 indicates a perfect model and a score of 0 shows the model predictions are random. A negative score indicates disagreement between observations and predictions. Also, the MCC score is symmetrical, so no special treatment is applied to a class based on imbalance. This means the MCC score remains unchanged even if the positive and negative are switched. These statistics are discussed with the relevant score in the results section.

Precision is defined as the ratio between the true positive and the total predicted number of samples that are indicated as positive

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

TABLE 3. Comparison of precision, recall, and F_1 score.

Classifier	Not Stress (0)			Stress (1)			Weighted Avg		
	Precision	Recall	F_1	Precision	Recall	F_1	Precision	Recall	F_1
Logistic Reg.	0.67	0.98	0.80	0.57	0.03	0.06	0.64	0.67	0.56
Decision Tree	0.71	0.96	0.81	0.70	0.19	0.30	0.70	0.70	0.64
Rand. Forest	0.70	0.99	0.82	0.94	0.14	0.25	0.78	0.71	0.63
K-NN	0.94	0.94	0.94	0.88	0.87	0.88	0.92	0.92	0.92
SVM	0.71	0.97	0.82	0.78	0.19	0.30	0.73	0.71	0.65
XGBoost	**0.998**	**0.998**	**0.998**	**0.997**	**0.995**	**0.996**	**0.997**	**0.997**	**0.997**

Recall is the ratio of true positives to the total actual number of samples reported as positive.

$$Recall = \frac{TP}{TP + FN} \tag{4}$$

The F1 score is related to the harmonic mean of the precision and recall.

$$F1\ score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{5}$$

We also presented a comparison of per class and average precision, recall, and F1 score in Table 3. Precision also called positive predictive value, measures the fraction of true positives among the total retrieved instances (TP and FP). Recall, also known as sensitivity, is a fraction of true positives among relevant instances (TP and FN). The F1 score is a balanced assessment of precision and recall, given by their harmonic mean.

IV. RESULTS

This section discusses the results of different stress prediction models. The evaluation of various machine learning classifiers for stress prediction yielded insightful results. The performance of each classifier was assessed based on precision, recall, and F1 score for both stressed (Class 1) and not stressed (Class 0) categories, as well as their weighted averages across both classes in Table 3. The Logistic Regression model demonstrated moderate precision (0.642) and recall (0.675), with an overall F1 score of 0.561. While it showed a high recall for Class 0 (0.987), its performance in identifying stressed cases (Class 1) was notably lower, with a recall of just 0.036. The Decision Tree classifier exhibited a balanced performance with a weighted average precision of 0.708, recall of 0.709, and an F1 score of 0.649. It performed well in predicting not stressed cases but was less effective in identifying stressed ones. The Random Forest model showed improvement, particularly in precision for stressed cases (0.948), but its recall was low (0.144), resulting in a weighted average F1 score of 0.636. The K-Nearest Neighbors classifier showed high scores across all metrics, achieving a precision of 0.922, a recall of 0.922, and an F1 score of 0.922. Its balanced performance in both classes indicates robustness in stress prediction. Support Vector Machines also showed good results, particularly in precision for stressed cases (0.781). However, similar to other models, its recall for stressed cases was lower, leading to a weighted average F1 score of 0.652. The XGBoost model demonstrated exceptional performance, with nearly perfect scores across all metrics. It achieved a precision of 0.997, a recall of 0.997, and an F1 score of 0.997. Its near-perfect classification in stressed and not-stressed categories highlights its superior predictive capability.

TABLE 4. Accuracy and MCC score of different models.

Classifiers	Accuracy (%)	MCC
Logistic Regression	64.20	0.074
Decision Tree	70.80	0.255
Random Forest	78.40	0.302
K-Nearest Neighbors	92.20	0.823
Support Vector Machines	73.40	0.284
XGBoost	**99.70**	**0.994**

Table 4 shows accuracy and Matthew's correlation coefficient (MCC) score achieved through grid search for respective models. Distinct performance variations were evident in the comparative analysis of machine learning classifiers for stress prediction. Logistic Regression and Decision Tree, with an accuracy of 64.20% and 70.80%, respectively, demonstrated moderate predictive abilities; however, their lower MCC values (0.074 for Logistic Regression and 0.255 for Decision Tree) indicated limited efficacy in distinguishing stressed and not stressed states. In contrast, Random Forest and Support Vector Machines (SVM) exhibited higher accuracy (78.40% and 73.40%, respectively) and better MCC scores (0.302 for Random Forest and 0.284 for SVM), suggesting improved classification capabilities in Table 3. A significant increase in performance was observed with K-Nearest Neighbors (KNN), achieving a robust accuracy of 92.20% and an impressive MCC of 0.823, reflecting its strong predictive power. However, the standout performer was XGBoost, which outperformed all other models with a remarkable accuracy of 99.70% and an MCC of 0.994. This highlights XGBoost's exceptional ability to accurately predict stress levels for our proposed framework, far surpassing the capabilities of traditional models like Logistic Regression and Decision Tree and more complex models like Random Forest and SVM in Table 3.

V. DISCUSSION

The findings from our study provide valuable insights into the development of a stress-monitoring framework for workers in high-stress assembly line environments using IoT and machine learning. By leveraging physiological signals collected through wearable devices, such as heart rate, respiration rate, and skin conductance, we aimed to predict stress levels in real-time to benefit worker health and well-being, as well as improve productivity in smart factory settings. Our study builds upon existing literature that explores the use of wearable technology and machine learning for stress monitoring in various industries. While previous research has highlighted the potential of these approaches, our study contributes by focusing specifically on assembly line workers in high-stress environments.

The utilization of machine learning algorithms, such as Logistic Regression, Decision Trees, Random Forest, K-Nearest Neighbors, Support Vector Machines, and XGBoost, allowed us to compare their performance in predicting stress levels. The results of our study align with previous findings indicating that more complex machine learning models tend to outperform traditional models in stress prediction tasks [12, 15]. For instance, the XGBoost model demonstrated exceptional performance, achieving near-perfect scores across all metrics. The implications of our findings for industry practice are significant. By deploying a stress-monitoring framework powered by machine learning algorithms, manufacturing companies can proactively address stress-related issues among their workforce. The real-time prediction of stress levels allows for timely interventions to mitigate stressors and prevent adverse effects on worker health and productivity. Furthermore, the insights generated by our study can inform the design of intervention strategies tailored to the specific needs of assembly line workers. For example, identifying tasks or workstations associated with higher stress levels can facilitate targeted interventions, such as workload redistribution, task rotation, or implementation of relaxation techniques. Moreover, the integration of our stress-monitoring framework into existing production systems can enhance overall operational efficiency. By identifying and addressing stress-related bottlenecks, companies can optimize production processes, reduce downtime, and improve product quality.

Moreover, the predictive capabilities demonstrated in this research could be adapted for personalized stress management programs. Employees could be provided with tailored interventions and recommendations by continuously monitoring and analyzing individual stress levels. It can also be employed in high-stress work environments, such as healthcare, emergency services, and aviation. While these future implications hold promise, further research should seek to adapt and implement these technologies in real-world settings while addressing challenges like data privacy and user acceptance.

VI. CONCLUSION

With the increase of advanced technologies and analytical capabilities, coupled with the continuous efforts to innovate, more machine learning models are being developed in the manufacturing domain. However, only a small number of those models emerge into the assembly line. This study aimed to investigate the utilization of wearable technology and machine learning algorithms for monitoring and predicting real-time stress levels among workers in an assembly line environment. The findings demonstrated the potential of machine learning algorithms to classify data and predict stress levels accurately based on physiological signals collected from wearable sensors. Through hyperparameter tuning using grid search, we achieved an accuracy of 99.70% and an MCC score of 0.994 for the XGBoost algorithm. These results indicate our methodology can potentially improve worker safety, well-being, and productivity. The proposed system can also help achieve job satisfaction and reduce absenteeism in high-stress work environments. Overall, the study highlights the importance of leveraging technology to mitigate the adverse effects of workplace stress from a unique technological perspective, thus promoting healthier and more efficient work environments for employees in smart factories of the future. The main requirement of this research is the availability of sufficient data. Also, challenges are associated with implementing our solution, such as the cost of acquiring the devices and the complexity of integrating smart objects in dynamic environments like assembly lines. However, it is essential to underscore that the information utilized in this investigation did not originate from an actual industrial setting since health data are confidential and industries usually impose constraints on sharing such data. Despite these limitations, this research suggests several future scopes, including further research to refine and optimize the effectiveness of the proposed system. Future work could explore and integrate other technologies, such as virtual and augmented reality, to enhance worker safety and well-being. Developing personalized stress management strategies based on individual stress patterns can also be another extension of this work.

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