Journal of Theoretical and Applied Information Technology
15[st] July 2026. Vol.104. No.13

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

A REAL-TIME IOMT-BASED WEARABLE SYSTEM FOR SIMULTANEOUS STRESS AND FATIGUE DETECTION IN UNIVERSITY STUDENTS USING PHYSIOLOGICAL SENSORS AND MACHINE LEARNING

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ABSTRACT

The increasing lack of knowledge of the impact of stress and fatigue and how they can affect students' daily life has led to an increase in mental illnesses like anxiety, depression, and social anxiety and less productivity. Furthermore, they exacerbate physical illnesses especially hypertension, cardiovascular disorders, strokes, and obesity. In response to these growing concerns, this research proposes an Internet of Medical Things (IoMT)-based system to detect stress and fatigue in a real-time environment. This system collects physiological data via vital sensors. These data are used by machine learning (ML) algorithms to detect stress and fatigue and predict the students' mental health at an early stage. Furthermore, the proposed system alerts students and suggests recommendations to reduce or prevent stress and fatigue levels. These alerts and recommendations assist students in maintaining their mental health before conditions deteriorate. This study proposes a real-time IoMT-based wearable system combining multiple physiological sensors and machine learning algorithms for the simultaneous detection of stress and fatigue in university students. Our work differs from prior work that considers single condition or limited physiological signals, in the integration of multiple biosignals, the system provides real-time personalized alerts and recommendations. Moreover, we validate the proposed prototype through experiments involving real students in realistic scenarios. The obtained results indicated strong correlations between HR and SpO2. RF and KNN outperformed other models in terms of accuracy scores.

Keywords: *Wearable Device, Stress Detection, Fatigue Prediction, Machine Learning, Biosignals, Sensors, IoMT.*

1. INTRODUCTION

With the rapid advancement [1], the overuse of technology can also harm college students' psychology. According to the World Health Organization, depression and anxiety caused by stress cost the global economy over $1 trillion USD each year in lost productivity. Furthermore, a 2023 survey by the American Psychological Association reported that 79% of college students experience frequent stress and 61% report feelings of constant fatigue. These issues are mainly due to the overuse of technology and lack of digital balance [2][3]. Such stress can lead to sleep problems and continuous tiredness, which could negatively affect students' academic performance, mental health, and overall well-being.

Stress is a psychological state of anxiety or mental tension that arises when challenging situations occur [4]. Stress is a natural adaptive response that mobilizes cognitive and physiological resources to cope with perceived demands or threats. People experience stress to varying degrees, but their coping responses largely determine its impact on well-being. In educational environments, heightened stress can hinder students' capacity to relax and is frequently associated with adverse emotional states, including anxiety and irritability, alongside diminished attention and concentration. Furthermore, stress may manifest through somatic symptoms, such as headaches, musculoskeletal pain, gastrointestinal discomfort, and sleep disturbances [5]. Moreover, persistent or chronic stress has been demonstrated to aggravate existing medical conditions [6]. In addition, it may precipitate or intensify mental health disorders, such as anxiety and depression. Thereby increasing the need for timely access to appropriate healthcare services.

Fatigue [7] is an extreme sense of tiredness and diminished energy that can disrupt an individual's routine activities. Individuals are experiencing fatigue may perceive themselves as weak, exhausted, lethargic, or depleted. Furthermore, they may they may experience difficulties with speech or concentration, short-term memory deficits, and mood or emotional fluctuations. Fatigue can result from various causes, including anemia, poor nutrition, pain, anxiety, depression, insufficient sleep, thyroid disorders, and taking certain medicines [8]. Therefore, stress and fatigue significantly contribute to diminished student productivity and several psychological and physiological disorders [9].

Many people underestimate the seriousness of mental illnesses and fail to recognize their profound impact [4] [10]. In reality, mental health conditions can be excruciatingly painful. In addition, excessive stress can lead to physical and mental health issues such as cardiovascular diseases. One of the most significant issues with mental illness is that its effects are frequently invisible [11]. As a result of this, it is difficult for people to notice or take seriously. Many people struggle to comprehend the challenges they are going through or how to seek help. It is essential that we shed light on this issue in order to raise awareness and investigate the best approaches to handle and advocate for mental health effectively. Therefore, it is essential to develop an AI-assisted system using IoMT technologies that can help detect and predict students' mental state early on [12].

Adverse psychological health conditions [13] comprise depression, chronic stress, anxiety, anger, pessimism, and dissatisfaction with daily life. Furthermore, these conditions are linked to potentially detrimental biological responses, such as arrhythmias, heightened gastrointestinal issues, elevated blood pressure, inflammation, and diminished coronary blood flow.

The Internet of Medical Things (IoMT) [14] refers to a network of interconnected medical devices and objects that are equipped with electronics, circuits, software, and sensors. This network connectivity allows objects and devices to gather and share data. IoMT [15] has significantly advanced methods for monitoring, detecting, and predicting stress and fatigue through the use of wearable sensors. Analyzing the pattern of observed parameters allows for the anticipation of the health conditions. This can assist patients who do not require direct communication with their physicians when their condition is not critical.

Despite advances in health-monitoring technology, existing solutions often lack sufficient, personalized, real-time alert systems that proactively support people in managing stress and fatigue. Based on this research gap, we formulated the following research questions: To what extent can the IoMT and ML-based solutions predict the psychological status of the person? And can they mitigate the associated risks before they worsen? To answer these questions, we proposed a solution that employed ML algorithms, such as KNN, RF, DT, and SVM, to help analyze biometric data accurately. The proposed solution collected biometric data using several IoMT devices and sensors, including an ESP32, an AHT10 skin temperature sensor, a MAX30102 biomarker for measuring heart rate and oxygen levels, a GSR sensor for measuring skin response, and an MPU6050 for measuring movement and balance. The proposed solution can detect and predict the person's psychological state, send real-time alerts to prevent feeling stressed or fatigued, and represent a qualitative leap in the field of smart mental health.

This study introduces four scientific contributions as follows. First, a real-time IoMT-based wearable device was designed and implemented to integrate multiple physiological sensors for continuous monitoring of stress and fatigue. Second, a machine learning framework was developed to utilize Random Forest, KNN, Decision Tree, and SVM classifiers to predict users' psychological conditions using real-time physiological measurements. Third, to enable early intervention before stress and fatigue become severe, the proposed system provides personalized alerts and recommendations. Finally, the proposed system is experimentally validated using university students under realistic stress, fatigue, and relaxation scenarios.

The focus of this study is to design, implement, and run an experimental evaluation of the proposed wearable IoMT system. The study does not aim to provide clinical diagnosis, psychiatric treatment, or long-term psychological assessment. Furthermore, the study is limited to physiological signals collected from wearable sensors and does not incorporate contextual information such as sleep quality, environmental conditions, academic workload, or behavioral history, which remain promising directions for future research.

The rest of the paper is organized as follows: the next section presents the related work. Section 3 presents the architecture of the proposed solution. Section 4 outlines the methodology for conducting this research. Section 5 presents the experiment, participants, and how it was set up. Section 6 then presents results gained from this research. Section 7 discusses the findings of the experiments. Section 8 concludes the research and presents the future work.

2. RELATED WORK

Previous studies highlight the importance of using wearable devices, IoT technologies, and AI in monitoring for detecting stress and fatigue. Heart rate sensor, skin conductance sensor, and body temperature sensor have been used to analyze users' mental states. Many models achieved high accuracy, demonstrating the effectiveness of systems in stress prediction and mental health support. For example, Taskasaplidis et al. [16] presented a comprehensive review of the latest literature and developments in stress detection methods through extensive and holistic research on stress response. This review focused on the Autonomic Nervous System (ANS) and Hypothalamic-Pituitary-Adrenal axis (HPA). Furthermore, this review explored the exploitation of various methods, technologies, and data analysis systems to understand stress in a multifaceted and comprehensive manner. Moreover, Kakhi et al. [17] reviewed the research works from 2015 to 2024 on fatigue detection. Moreover, the combination of AI and wearable devices has dramatically improved the accuracy and ability to monitor fatigue in real-time settings. They demonstrated the research challenges facing the fatigue detection field. Lazarou et al. [18] emphasis was placed on examining and critically evaluating the existing research and literature on stress prediction. Physiological data analysis and wearable devices assume a pivotal role in monitoring stress. The review acknowledges their effectiveness in providing individuals with immediate feedback on health indicators.

Tyulepberdinova et al. [19] showed that stress harms emotional and physical health, causing sleep issues, irritability, and self-harm. It weakens immunity, lowers quality of life, and activates the "fight or flight" response. Wearable IoT devices with sensors like PhotoPlethysmoGraphy (PPG) and GSR monitor stress indicators such as blood volume and skin conductivity. One such device, using nine sensors and an FPGA, which is a Field-programmable gate array with Firebase support. It achieved 92% accuracy in trials to determine stress biomarkers. These technologies aid chronic disease management, athletic performance, and student stress monitoring.

Wijsman et al. [20] found that the common work-related health issues in Europe are stress, depression, and anxiety. They are linked to hypertension, heart disease, and weakened immunity. In a study with 30 participants exposed to stress-inducing tasks, Electrocardiogram (ECG) and respiration data were collected via a chest belt. Features, such as heart rate Variability (HRV), respiration frequency, and electrodermal activity were analyzed using sliding windows and z-score normalization. Despite challenges from using multiple stressors, the system achieved almost 80% accuracy in detecting stress. Therefore, complex multi-modal physiological monitoring is valuable for stress detection.

Katarya et al. [21] highlighted the role of wearable tech and ML in stress detection. Smartwatches were used to track signals, such as HRV, GSR, skin temperature, and sleep. Stress causes changes such as increased heart rate, glucose levels, and skin conductance. ML algorithms, such as SVM, KNN, LR, and RF classify stress states, with unsupervised methods handling unlabeled data. Furthermore, combining signals, such as HRV and GSR improves accuracy over single-signal models. Moreover, the study also explored feature selection and signal processing to enhance real-time, personalized mental health monitoring.

Al-Atawi et al. [22] proposed a novel ML-based system termed “Stress-Track". The Stress-Track system tracked stress levels of an individual. In their experiments, they collected body temperature, sweat, and motion rate during physical activity. Their system achieved an impressive accuracy score of 99.5% using Gradient Boosting and RF algorithms. The data are to cloud storage using WIFI for analyzing.

Moshawrab et al. [23] reviewed the solutions of monitoring and detection of occupational physical fatigue using smart wearables. They addressed possible challenges and future directions. Researchers have used signals like HR, ElectroMyoGraphy (EMG), HRV, motion data, skin temperature, ElectroEncephaloGram (EEG), and jerk metrics. EEG stands out to directly assess brain activity linked to fatigue and relaxation. Since fatigue is often underestimated, real-time tracking is crucial for safety and health.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

The study emphasizes the need for accurate, continuous monitoring in workplace settings.

Utilizing heartbeat rate, Pandey, P.S. [24] proposed a prototype to determine stress in advance. When a person is truly in danger, IoT and ML-based solutions are used to signal the emergency. ML is used to estimate the patient's state and IoT is employed to notify the patient of his severe stress. Stress is known to cause a decrease in the immune system and in every measure of performance. Furthermore, the prototype developed identifies a person as stressed based on his heart rate variability. It can also aid in the identification of change patterns in a person's heart rate while exercising in the gym.

Talaat and El-Balka [15] examined the application of IoT technologies in the health industry. A stress monitoring approach was developed using ML and wearable devices. The proposed approach explored the degree to which it is used to enhance conventional practices in various health fields and the extent to which IoT may raise the standard of healthcare services. Moreover, this proposed approach can help improve the quality of healthcare delivered by healthcare institutions. The findings show that RF is the best classifier in this approach compared to the other ML algorithms.

Pabolu et al. [25] developed an IoT-based worker's work fatigue recognition system to recognize the real-time fatigue status of assembly line workers. The system supports the assembly line manager or supervisor while finding and facilitating the assembly line's fatigued workers. The system shows low prediction accuracy scores. Six ML algorithms were employed in this research. The linear regression model achieved the highest accuracy score.

Kim et al. [26] used the DeepAR model and the Temporal Fusion Transformer (TFT) Model and Ensemble model. The research study investigated the integration of the IoT and ensemble learning methodologies to enhance real-time fatigue monitoring in the construction industry. The research study combined PPG and EEG sensor data with a Learning ensemble model to monitor and predict physical fatigue and mental fatigue in real-time.

Although all the listed research has demonstrated the usefulness of wearable devices and IoT technologies in stress and fatigue direction, nevertheless, the studies exhibit notable limitations. For instance, the absence of real-time, personalized alert systems and limited sensor data, as opposed to treating stress and fatigue as distinct entities, despite their significant similarities. In response to these shortcomings, our research proposes the development and implementation of a real-time IoT-based wearable device integrating four physiological sensors. The device collects and processes live physiological data, predicts stress and fatigue using ML, and provides immediate suggestions. In contrast to earlier work, our system was tested with actual students in realistic settings, which helps confirm both its feasibility and accuracy. Table 1 summarizes how our approach compares with prior studies in terms of datasets, sensors, algorithms, and main findings.

2.1 Research Gap and Problem Statement

The effectiveness of wearable devices, IoMT technologies, and machine learning for stress and fatigue monitoring has been proven in previous studies. However, there are several important limitations. Existing approaches focus on either stress or fatigue, use only a few physiological sensors, or perform offline analysis without providing real-time personalized alerts and recommendations. Moreover, few studies have validated complete wearable IoMT prototypes with real participants in realistic settings.

To overcome these limitations, this paper proposes a real-time wearable system based on the Internet of Medical Things (IoMT) which combines a number of physiological sensors and machine learning algorithms to simultaneously detect stress and fatigue. The proposed framework continuously monitors physiological signals, predicts users' psychological conditions in real time, and provides personalized alerts and recommendations to support early intervention and improve student mental well-being.

TABLE I. SUMMARY OF RELATED WORKS

Reference	Dataset	Sensors	Algorithms	Main Result	Limitations and Issues
Tyulepberdin	wearable IoT	ECG, EMG, EEG,	SVM, KNN,	92%	Limited sample size,

Reference	Dataset	Sensors	Algorithms	Main Result	Limitations and Issues
ova et al, (2025) [19]	system. 9 sensors and 30 participants	GSR, PPG (MAX30102), Glucose sensor, Temp sensor, Pressure sensor, Pulse sensor	RF, DT Logistic Regression, MLP		complexity of sensor integration
Wijsman et al, (2011) [20]	30 subjects, 9 physiological features used, 7 principal components.	ECG, Respiration, Skin Conductance, EMG	Fisher's Least Square, Linear Bayes Normal, and Quadratic Bayes Normal KNN	80%	High error rate, no variance in gender, small sample size, no real-world validation
Katarya et al, (2020) [21]		HRV, GSR, Skin Temperature, Sleep Patterns	SVM	92.75%	GSR sensors are rarely found in commercial smartwatches. Using Skin temperature in the summer season may not the ideal option to detect stress
Al-Atawi et al, (2023) [22]	4 Features 2001 Samples	Skin temperature, Sweat, and Motion rate	RF, Gradient Boosting, sStacked Ensemble Method	99.5%	scalability and resource requirements challenges when the system is implemented in real-world scenarios
Pandey, P.S., (2017) [24]		Heart Rate Variability	Logistic Regression (LR), SVM, Naive Bayes, VF – 15	LR and SVM, an accuracy of 66 % and 68 %, respectively	Inadequate data
Talaat et al, (2023) [15]	2001 samples, with 4 features (humidity, temperature, step count and stress levels)	ECG, Infrared sensors for blood glucose, Hypertension monitoring, Smoking behavior analysis	RF, OSM Classifier, XGBoost, DT	RF and OSM classifiers achieved 100% in both accuracy and ROC-AUC. XGBoost 96.3%, and DT 92% for the accuracy measure	scalability and resource requirements challenges when the system is implemented in real-world scenarios
Pabolu et al, (2024) [25]	Data were collected from 11 participants (6 males and 5 females).	Electroencephalography - EEG, Electroencephalography - EEG	Linear Regression, Polynomial SVM, DT, RF, Naïve Bayes	Symmetric Mean Absolute Percentage Error sMAPE = 0.0008	The learning dataset is small, and the corresponding prediction accuracy is low

3. THE ARCHITECTURE OF THE PROPOSED SYSTEM

The primary objective of the proposed system is to design a wearable device that integrates five sensors: a heart rate and blood oxygen saturation sensor, a skin temperature sensor, a body movement sensor, and a skin conductance sensor. The wearable device collects measurements via the sensors and stores the collected data in local memory. Moreover, the system allows for real-time processing. Then, the system will determine whether the user is experiencing stress, fatigue, or relaxation. Based on the user status, the system will generate alerts and suggestions to help reduce stress and fatigue or prevent their onset. Figure 1 shows the main components of the proposed system.

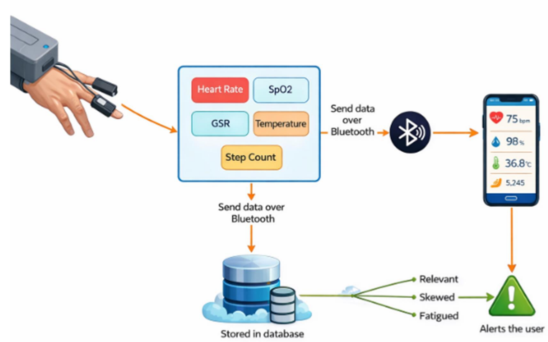

Figure 1. The System Architecture

Figure 2 shows the prototype of the IoT-based wearable device, which is used for a real-time detection of stress and fatigue. The device was fully developed in-house using an ESP32 microcontroller, integrated biosensors, and a 3D-printed enclosure for wearable use.

Journal of Theoretical and Applied Information Technology
15st July 2026. Vol.104. No.13

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

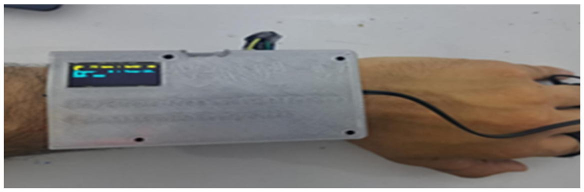

Figure 2. The actual prototype of the wearable device

3.1 Overview of System Hardware

Several sensors are demonstrated in this section, the resources utilized to confirm their functionality, and how they are integrated to achieve optimal results.

3.2 Heart Rate and Blood Oxygen Saturation Sensor

The study presented in [24] demonstrate that can determine a person is stressed or not using only Heart Rate Variability (HRV) measure. According to that, we can measure HRV from the data we get from the sensor (MAX30102) using mathematical equations to help us make our decision. The MAX30102 is a compact sensor that combines pulse oximetry and heart-rate monitoring. It features built-in LEDs, photo detectors, and low-noise electronics with ambient light rejection. The sensor operates on a 1.8 V supply with a separate 3.3 V supply for the LEDs and communicates via an I²C interface. It is ideal for wearable devices because of its low power consumption and small size. In addition, the same sensor is used to measure the blood oxygen saturation. According to [16], stress and anxiety alter the respiratory rate, which alters oxygen saturation in the blood. This leads to a temporary decrease in oxygen saturation to 94-95%.

3.3 Skin Temperature Sensor

According to [27], the studies showed that the person experiencing stress has a drop in their temperature, especially in the extremities. Based on that, we chose this vital sign and used the skin temperature sensors (AHT10), allowing us to detect the temperature variations to determine whether a person is stressed. We particularly use the AHT10 sensor to monitor temperature variations and detect stress-induced changes. Furthermore, it is designed with a temperature measurement range of -40ºC to 85ºC. To ensure reliable and precise readings, the sensor provides a typical temperature accuracy of ±0.3°C. Within a voltage range of 3.3V to 5.0V, the sensor can communicate through the I2C interface, which simplifies the integration with various systems. The AHT10 sensor can detect stress-related temperature fluctuations based on subtle temperature changes. This leads to support real-time analysis of emotional and physiological states.

3.4 Body Movement Sensor

The study [28] mentioned that stress and anxiety can lead to changes in physical activity such as restlessness or decreased movement. By monitoring body movement, we can identify these behavioral indicators of stress. This sensor measures acceleration and rotation in three dimensions, which is useful for applications involving motion detection and orientation.

3.5 Skin Conductance Sensor

According to the findings of [29], sweating can happen as a response to fear or stress, which is why you might notice increased sweating. Based on this, the system monitor skin conductance variations to support its decision. Therefore, the most accurate position for placing the sensor is between the index and ring finger on the same hand, which allows for optimal contact with the skin. The GSR sensor accurately measures vital signs and responses associated with stress and fatigue detection. Due to sweating as a result of emotional arousal, the electrical conductance of skin increases. It provides valuable data for detecting emotional and physiological states related to stress and fatigue. Furthermore, the GSR sensor requires a 5V or 3.3V input voltage for operation and is designed to be used with external measuring finger cots to improve accuracy.

3.6 Model

The proposed solution is implemented based on the integration of a wearable IoT device with an ESP32 microcontroller and four essential biosensors:

- AHT10: It measures skin temperature.
- MPU6050: It detects body movement and orientation.
- GSR Sensor: It captures galvanic skin responses to monitor emotional vigilance and degrees of stress intensity.
- MAX30102: It measures heart rate and blood oxygen saturation magnitudes (SpO2).

Furthermore, real-time physiological data are collected using these sensors. These data are processed and analyzed to detect stress and fatigue patterns. To ensure efficient data flow from physical sensing to intelligent decision-making, Figure 3 illustrates a multi-layer architecture, which comprises three main layers:

- Sensor Layer: It is responsible for acquiring physiological signals from the user.
- Processing Layer: It executes data preprocessing and real-time analysis on the ESP32 microcontroller.
- Prediction Layer: It performs classification using trained ML-based models.

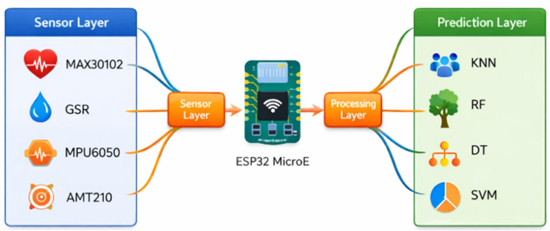

Figure 3. Multi-Layer Architecture for Physiological Signal Acquisition and ML-based Prediction

4. METHODOLOGY

As shown in Figure 4, the methodology steps we are following are:

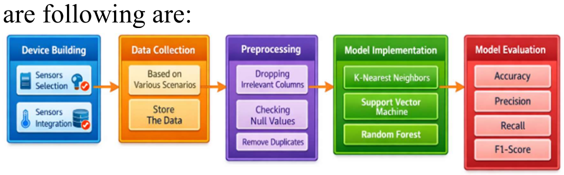

Figure 1. Machine-learning-based model methodology.

4.1 Device Building

According to [16], a lot of human body biomarkers and biological signal measurements are affected by stressful and fatigue-causing conditions, such as heart rate (HR), skin temperature, electrodermal activity (EDA), blood oxygen saturation (SpO2), and body movements. Based on them, we chose four sensors to measure them, MAX30102 sensor for heart rate and blood oxygen saturation measurement, AHT10 for skin temperature measurement, MPU6050 for body movement measurement, and GSR for skin response – EDA measurement. Sensors integration is the process that combines several data types from multiple sensors into a unified system. It improves accuracy and reliability of stress and fatigue monitoring and controlling.

4.2 Dataset Collection

We have collected the data from 14 individuals based on some scenarios, some when the person is relaxed or feeling comfortable, scenarios that are considered stressors, and fatigue-causing scenarios as mentioned in the experiment section. Then the data will be stored for further processing and analysis.

4.3 Dataset Preprocessing

A necessary step to clean and prepare the raw data for further analysis. It includes a lot of steps, such as dropping irrelevant columns, checking null values, removing duplicates and checking and dropping outliers. After loading the data, we dropped the timestamp column completely, checked for missing values and dropped them, verified data types of numerical columns and converted them to numeric, ensuring the labels to be numeric and scaled numerical features. Then we visualized the outliers in the dataset using boxplots so we could spot them, after that we visualized correlations between features using a heatmap.

4.4 Dataset Analysis and Model Training.

Since the data is preprocessed, it is ready to be analyzed in order to be able to train the model. Data analysis also performs some calculations and combines data for better results. In model training, the DT, KNN, SVM, and RF classifiers were used. Based on that, the trained model can subsequently predict and make decisions.

4.5 Model Testing and Evaluation.

The model's performance is evaluated using the benchmark matrices, such as accuracy, precision, recall, and F1 score. Accuracy is the proportion of correct stress or fatigue predictions to the total number of predictions. Precision is the ratio of the stress or fatigue predictions to the summation of true and false stress or fatigue. Recall is the ratio of the corrected predictions of stress or fatigue to the summation of true and false predictions. The F1 score represents the harmonic mean of precision and recall scores.

4.6 Machine Learning Classifiers

K- Nearest Neighbors (KNN) is a supervised ML classifier generally employed for data classification and regression tasks. KNN attempts to find the "k" closest data points (neighbors) to a given input. KNN makes predictions based on the majority class for classification or the average value for regression [30].

Support Vector Machine (SVM) is a type of supervised ML algorithm that can be used for both classification and regression tasks. SVM is great for classification tasks, but it can also handle regression problems. SVM's goal is to find the best hyperplane in an N-dimensional space that can

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

separate data points into different groups. SVM makes the space between the closest points of different classes as wide as possible [30].

Random Forest (RF) is a machine learning algorithm that uses a lot of decision trees to make predictions more accurate. Each tree examines distinct random segments of the data, and their outcomes are aggregated through voting for data classification or averaging for the regression task. Putting these trees together can make the model more accurate and cut down on its mistakes [30].

A Decision Tree (DT) is a picture that shows how different choices can help solve a problem and how different features are connected. The top of a DT tree is called the root, and it has a hierarchical structure. DT goes even further and splits into different possible outcomes [30].

5. EXPERIMENTS

Phase I – Comfort Enhancement

Deep breathing and body scan meditation [31][32] are used to gather data from participants in a relaxed state. Participants were instructed to engage in deep breathing exercises for 5 to 10 minutes to attain relaxation. This technique comprises three steps: inhaling for four seconds, holding the breath for seven seconds, and exhaling for eight seconds. In general, body scan meditation takes 5 to 20 minutes, during which the participant focuses on slowly and consciously observing sensations in different parts of the body [33][34].

Phase II – Stress Induction

Participants complete a memory-matching game under strict time constraints [35]. Moreover, participants engage in a rapid chess challenge with a visible countdown [36]. In addition, participants undergo a 15-minute simulated job interview [37]. Then, we record the participants' stress ratings and physiological indicators immediately before and after each task.

Phase III – Fatigue

Fatigue is one of the most common symptoms of dehydration. For instance, exercising increases water loss through sweating and breathing [38]. Therefore, participants were instructed to perform athletic exercises for 40 minutes.

Participants and Experimental Setup

A practical experiment involved 14 voluntary participants to validate the effectiveness of the proposed system for detecting stress and fatigue. The participants were aged between 19 and 24 years old. Moreover, participants were university students and included both male and female students. The experiments are performed as follows: The purpose of the study is explained to all participants. The ethical guidance was followed during the whole process. This process ensures that everything remains completely anonymous and confidential. Verbal consent was obtained from all participants prior to the experiment. Then, each participant wears the developed device during a series of predefined tasks designed to elicit relaxed, stressed, and fatigued states. The real-time physiological data were collected using the developed device. Furthermore, personal information was not collected. All data was stored and analyzed in an anonymized format.

6. RESULTS

In this study, we analyzed the relationships between physiological features and a target label, which represents psychological states. Physiological features include heart rate (HR), blood oxygen saturation (SpO_2), steps, temperature (Temp), and GSR. Moreover, we evaluated the performance of various ML models for stress and fatigue classification.

6.1 Feature Correlation Analysis

Clear relationships among the measured features are demonstrated through the feature correlation matrix. For instance, the HR and SpO2 features had a strong positive correlation (r = 0.65). This means they tend to increase together. The Steps and the target features had a mild positive correlation (r = 0.45), which means that physical activities might influence the target feature. In addition, the Temp and GSR features displayed a perfect positive correlation (r = 1.0) which indicates a direct relationship between them. Furthermore, the other feature pairs demonstrated weak correlations, with coefficients close to zero. Figure 5 illustrates the correlation coefficients among all the features. Stronger positive correlations are shown in red, while weaker or negative correlations are shown in blue.

Journal of Theoretical and Applied Information Technology
15st July 2026. Vol.104. No.13

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

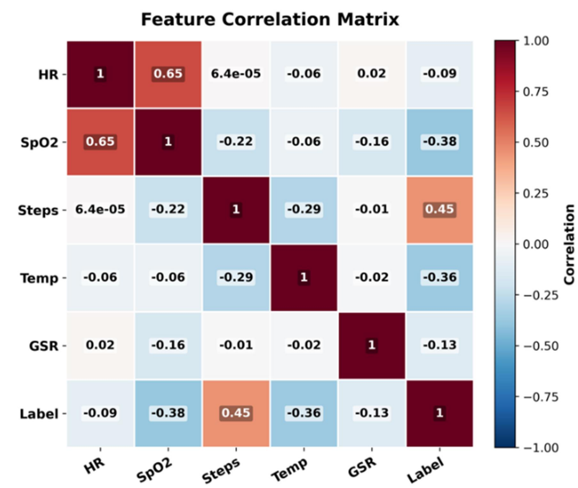

Figure 5. Correlation Matrix of Physiological Features

6.2 Feature Distribution Analysis

Figure 6 shows the physiological features, including HR, SpO_2, Temp, and GSR. These features show relatively tight interquartile ranges, which indicates consistent readings among participants. A few outliers suggest occasional spikes or drops, possibly due to emotional states. Furthermore, Steps had the widest variability and the most outliers, which reflects large differences in movement levels across participants and scenarios. Figure 6 displays the spread and variability of each feature that identify consistent metrics and potential anomalies.

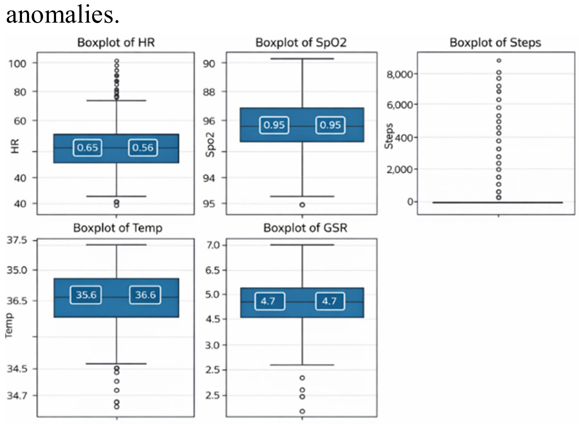

Figure 6. Boxplots of Features

6.3 Model Performance Comparison

We run several experiments to test the performance of the proposed approach using the ML classifiers (DT, RF, SVM, and KNN). The experimental results show that the RF classifier achieved the best performance with an accuracy of 93.47%. KNN obtained an accuracy score of 91.79%, followed by DT with an accuracy score of 90.56%. Furthermore, SVM performed with a lower accuracy score of 83.25%. These findings indicate that RF clearly outperforms the others, and SVM has limitations in handling overlapping data distributions. Moreover, Figure 7 compares the overall accuracy of each model.

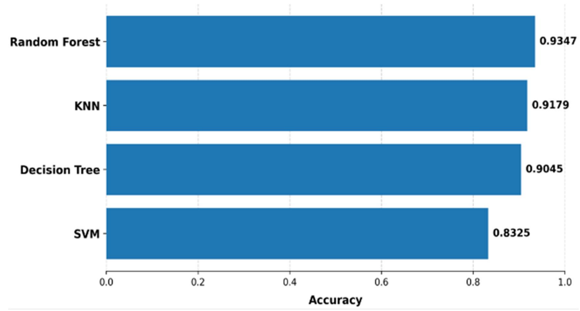

Figure 2. Model accuracy comparison

Figure 8 demonstrates confusion matrices for each classification algorithm. The confusion matrices highlight that RF and KNN had the most correct "stressed" and "fatigued" predictions. Figure 9 provides a detailed comparison of classification results. The results reinforce that RF is the most effective model. According to the obtained results, RF is suitable for real-time stress and fatigue prediction. These findings confirm the effectiveness of wearable biosensors in detecting mental fatigue and stress using ML.

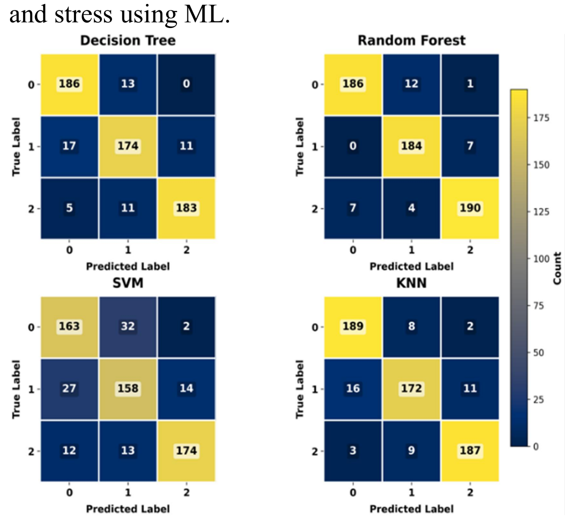

Figure 3. Confusion Matrices

Journal of Theoretical and Applied Information Technology
15st July 2026. Vol.104. No.13

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

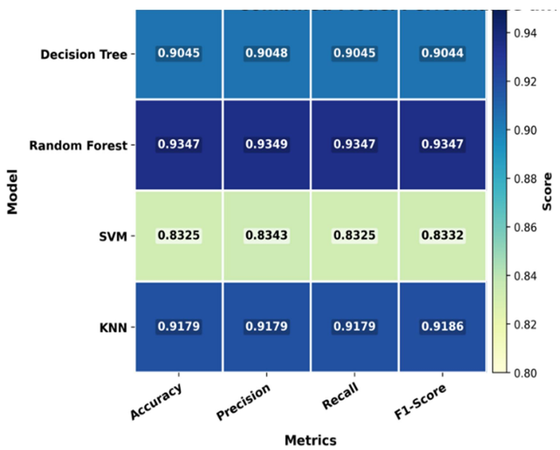

Figure 9. Results of model performance

7. DISCUSSION

The obtained results are generally consistent with previous studies that reported the effectiveness of wearable physiological sensors for stress monitoring. For example, Talaat and El-Balka [15] and Al-Atawi et al. [22] also observed that Random Forest achieved superior classification performance compared with several traditional machine learning algorithms. Our findings further confirm that ensemble learning methods are particularly suitable for handling heterogeneous physiological measurements because they effectively capture complex non-linear relationships among multiple biosignals.

Nevertheless, the prediction accuracy achieved in this study differs from some previously reported results. While the studies [22] and [15] reported higher classification performance using different physiological attributes and datasets. These differences highlight a critial issue in using AI techniques in this field. It indictes that prediction accuracy is strongly influenced by several factors such as participant characteristics, sensor configurations, feature selection, data preprocessing techniques, and experimental protocols.

Compared with previous studies that focused exclusively on stress detection or fatigue monitoring, our work simultaneously investigates both psychological conditions within a unified IoMT framework. Moreover, several existing approaches performed offline analysis while the proposed system provides real-time monitoring, automatic alerts, and personalized recommendations. These features make the proposed system more suitable for continuous health monitoring in educational environments.

Although Random Forest achieved the highest classification accuracy, the experimental results also reveal several research challenges. A possible feature redundancy as result to the strong positive correlation between temperature and GSR. Moreover, the large variability in movements suggests that context features such as exercise intensity or normal daily activities may affect the prediction accuracy. Based on these observations, future intelligent health-monitoring systems should integrate contextual information and physiological measurements to improve prediction reliability.

The major findings of this study offer valuable insights into the relationship between physiological attributes and stress and fatigue detection in students, as well as the efficacy of ML-based models in predicting mental health conditions. The strong positive correlation between Heart Rate (HR) and Blood Oxygen Saturation (SpO2) indicates that HR and SpO2 are strongly correlated, possibly indicating the body's response to stress or physical activity.

The box plot analysis indicated that Steps had the highest variability among the attributes, with a large interquartile range and many outliers. The variability in Steps indicates the varying activity levels of students, which may affect stress and fatigue in different ways for different students. For example, higher step counts may be indicative of physical activity that reduces stress in students, while in others, it may be indicative of overexertion, which may cause fatigue. HR, SpO2, Temperature, and GSR, on the other hand, had a relatively compact distribution, indicating that these attributes are more consistent and thus suitable for real-time monitoring.

The performance of the ML models indicates that the proposed IoT device could be beneficial for early stress and fatigue detection. RF and KNN resulted in the highest accuracy. The above results demonstrate that ensemble models such as RF are appropriate for dealing with complexity and variability in physiological signals, as they are capable of modeling non-linear relationships and interactions between variables. Conversely, the poor performance of SVM suggests that linear models are not effective for dealing with the complex patterns in the dataset, especially for class 1 (stress), where errors in classification were more common.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

There are several practical implications of the proposed system as follows: (1) Practical implications for smart healthcare and IoMT. Hence, the proposed IoMT-based wearable system has great practical significance for the future development of smart healthcare solutions. Furthermore, the integration of multiple physiological sensors with machine learning algorithms makes the system capable of continuous, non-invasive and real-time monitoring of stress and fatigue without the need of frequent visits to the clinics or expensive medical equipment. This capability enables a shift from reactive health care, where intervention is initiated after symptoms have become severe, to proactive health care, where early detection allows timely preventive actions. Moreover, the convergence of wearable sensing technologies and intelligent decision-making offers healthcare professionals objective physiological markers that may help in monitoring people at risk of developing stress-related physical and psychological disorders. Thus, the proposed system contributes to the advancement of personalized healthcare: enabling continuous monitoring of physiological conditions and providing immediate recommendations tailored to the user's current mental state.

(2) Practical implications for the surveillance of mental health at university. The proposed system presents significant benefits for educational institutions that seek to enhance student well-being and academic performance. Stress and fatigue levels of college students increase due to academic pressure, examinations, workload, and social challenges without timely identification. The developed wearable device is capable of monitoring the physiological conditions of the students continuously during their daily activities, and can give alerts in real time before the stress and fatigue reach critical levels. Early interventions can encourage students to develop healthy behaviors, manage time better, seek counseling services when needed, and reduce long-term effects of psychological stress that is not managed. Moreover, aggregated and anonymized monitoring data could assist university health centers and student counseling units to detect periods of increased psychological pressure, thereby allowing institutions to develop evidence-based wellness programs and preventive interventions, while protecting students' privacy and confidentiality. These practical applications showcase the promise of IoMT technologies for smarter, data-driven mental healthcare in today's educational settings.

Despite the encouraging results, there are a number of limitations that must be pointed out. (1) The fact that there is a perfect correlation between temperature and GSR could be a problem in terms of the independence of these variables, potentially increasing the performance of the model by providing redundant information. (2) The variability of the dataset in terms of steps could imply that the contextual information, such as activity type or time of day, was not entirely captured. The reliability of the proposed approach may be potentially impacted. (3) The accuracy scores of the proposed approach are not optimal. Therefore, including new features such as sleep patterns or self-reported stress levels could potentially improve the accuracy. (4) A small population of students participated in the study. It is potentially not entirely representative of the larger population with different stress responses.

8. CONCLUSION

This paper proposed, implemented, and experimentally evaluated a real-time Internet of Medical Things (IoMT)-based wearable system. This system is used for the simultaneous detection of stress and fatigue in university students using multiple physiological sensors and machine learning techniques. Furthermore, the experimental results demonstrate that Random Forest achieved the highest prediction accuracy among the evaluated classifiers. The experimental findings confirm the suitability of ensemble learning methods for analyzing heterogeneous physiological signals collected in real time. Furthermore, the following features can be provided by the proposed system: continuous health monitoring, personalized recommendations, and early alerts that may help students manage stress and fatigue before their conditions become more severe.

The proposed IoMT device demonstrates the potential to be of considerable assistance in the early detection of stress and fatigue, which in turn can assist in the management of students' mental health. By notifying the user of the expected stress and fatigue conditions and recommending involvements, the device is able to counteract the increasing number of cases of mental health issues. Although the device has made considerable contributions, it has also had some limitations, such as feature redundancy, variability in the dataset, and average accuracy of models.

To sum up, this study proposes a real-time IoMT-based wearable system combining multiple physiological sensors and machine learning algorithms for the simultaneous detection of stress and fatigue in university students. Our work differs from prior work that considers single condition or limited physiological signals, in the integration of multiple biosignals, the system provides real-time personalized alerts and recommendations. Moreover, we validate the proposed prototype through experiments involving real students in realistic scenarios.

Several future research directions can be follow to improve the performance and usefulness of the IoT device, future studies will concentrate on the following areas: Increasing the dataset and diversity by testing it on a larger and more diverse population, which will help to improve the generalizability and accuracy of the model. Incorporating more contextual features, such as (ambient temperature, noise level) and their own level of stress they are experiencing, which will help to improve the accuracy of the model by providing more context. Feature optimization will be used to eliminate redundancy between features such as temperature and GSR. Exploring the importance of using advanced deep learning models (Convolutional Neural Networks (CNNs) or Recurrent Neural Networks (RNNs)) [39]. It is better to capture complex patterns and improve accuracy. Adding a real-time functionality such as personalized relaxation reminders for high levels of stress or fatigue. This will provide more practical usefulness to the wearable IoMT-based device.

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