*International Journal on Recent and Innovation Trends in Computing and Communication*
***ISSN: 2321-8169 Volume: 11 Issue: 9***
***Article Received:** 25 July 2023 **Revised:** 12 September 2023 **Accepted:** 30 September 2023*

# Stress and Emotion Detection System Using IoT and Machine Learning with a Fuzzy Inference-Based Mental Health Risk Assessment Module

**Analene Montesines Nagayo**
Engineering Department,
University of Technology and Applied Sciences,
Al Musanna, Al Muladdah, Sultanate of Oman.
e-mail: analene@act.edu.om

**Mahmood Zayid Al Ajmi**
Engineering Department,
University of Technology and Applied Sciences,
Al Musanna, Al Muladdah, Sultanate of Oman.
e-mail: mahmood@act.edu.om

**Mai Mubarak Al Saadi**
Engineering Department,
University of Technology and Applied Sciences,
Al Musanna, Al Muladdah, Sultanate of Oman.
e-mail: maimubarak@act.edu.om

**Fatma Saleh Al Buradai**
Engineering Department,
University of Technology and Applied Sciences,
Al Musanna, Al Muladdah, Sultanate of Oman.
e-mail: fatmaalburadai@act.edu.om

**Abstract**— This research paper describes the conceptualization, deployment, and application of a stress and emotion detection system (SEDS) that utilizes emerging technologies including machine learning, the Internet of Medical Things (IoMT), and fuzzy logic. Particle Photon microcontrollers were used to collect and analyze data from non-invasive biosensing devices, input switches for behavioral, emotional, and cognitive stress indicators, and input signals generated by the machine learning-based facial identification sub-module, which detects an individual's emotional states (happy, sad/upset, angry/irritable, or nervous/scared). The acquired parameters were stored and made readily accessible using IoT cloud services and dedicated mobile phone applications. The emotional condition of an individual was assessed by the utilization of the Personal Image Classifier tool within the MIT App Inventor, which involved the analysis of facial expressions. Furthermore, the SEDS was integrated with a module for mental health risk assessment which employs fuzzy logic to categorize the user's stress-related psychological health threat level as very low, low, moderate, high, or extremely high based on the data collected. The customized smartphone application provided users specific recommendations for effectively managing their mental health, based on stress level assessments. When the SEDS determined that the level of mental health risk posed by stress was high, it automatically generated a referral notification and transmitted it via text message to the mental health care professional, facilitating the provision of appropriate psychological counseling. Based on the collected data, the stress and emotion detection system produced results that were comparable to those from the DASS21 stress scale. The system demonstrated an improved accuracy of 90% in a test involving thirty individuals who volunteered to participate. The machine learning-based emotion detection system achieved a classification accuracy of 86.67% in correctly detecting happy, neutral, sad, angry, or nervous feelings through the analysis of facial expressions. This research is designed to provide mental health care professionals such as guidance counselors, psychologists, and psychiatrists with the resources essential to facilitate the evaluation and treatment of mental health issues. It also aims to raise people's understanding and detection of psychological conditions through enhanced awareness initiatives.

**Keywords**- machine learning, internet of medical things, fuzzy logic, mental health risk.

## I. INTRODUCTION

Stress can manifest within the educational setting for both teachers and students due to a range of factors. These factors encompass heightened academic demands, the burden of overwhelming workloads, impending assessments, and the pervasive culture of peer competition [1]. Teachers encounter stress as a result of various reasons, including the demanding nature of their workload, the uncertainty surrounding their employment status, the behavior exhibited by students, a lack of social support, and insufficient educational resources [2],[3]. Elevated levels of stress can lead to diminished teaching effectiveness, increased rates of absenteeism, and cases of faculty members leaving their jobs. A study conducted by [4] has indicated that stress can give rise to various physical and mental health issues among teachers, encompassing conditions such as hypertension, heart disease, stomach ulcers, asthma, and psychological distress. College students, on the other hand, face stress as a result of academic requirements (exams, reports, and projects), limited support systems, and ineffective coping capacities, as described in [5]. According to the findings of [6] the introduction of online teaching and learning in response to the COVID-19 pandemic resulted in students experiencing varied degrees of stress, ranging from mild to severe. High levels of stress encountered by students have the potential to have a negative impact on cognitive functions, hindering the capacity to keep concentration, process information, and participate in analytical reasoning. Academic-related stress, if not managed appropriately, may contribute to the development of health problems, particularly chronic noncommunicable illnesses, due to a decrease in physical activity and an increase in unhealthy habits [7].

In light of the current circumstances, a stress and emotion detection system (SEDS) was developed and deployed utilizing the Internet of Medical Things (IoMT), machine learning techniques, and fuzzy logic. The system aims to enhance awareness regarding mental health care, employ dependable approaches for assessing mental health risks, and adopt a comprehensive approach to guide actions that prioritize the overall physical and emotional well-being of individuals. The stress and emotion detection system developed in this research shows significant improvements over the system presented in [8]. The prior approach relied primarily on IoT and GSM technologies to monitor stress levels and associated health hazards. In addition to the biosensors used in [8] to measure the thermal state of the body, arterial blood pressure, beating of the heart per minute, oxygen level in the blood, number of breathings per minute, and electrical conductivity of the skin, the Particle Photon-based SEDS received information from additional sensors such as pH and proximity IR sensors to further investigate the effect of stress on a person's health. Aside from acquiring behavioral, cognitive, and emotional stress indicators via input switches, the IoT-enabled system was linked to a machine learning-based emotion recognition module based on face features to detect happy, neutral, sad/upset, angry/irritable, and nervous/scared states. A fuzzy inference-based model was also integrated into the SEDS to assess mental health risk as very low, low, moderate, high, or extremely high based on physiological, emotional, cognitive, and behavioral stress markers. The parameters derived from sensor data, together with other stress indicators, are stored and can be accessed via an online platform. Furthermore, the monitoring of this data can be achieved in real-time by employing Internet of Things (IoT) cloud-based services and dedicated smartphone applications. The MATLAB program and custom-designed mobile applications provided a visual representation of the psychological health risk level associated with stress, along with suggestions for effectively managing stress. When the evaluated level of mental health risk was determined to be critical, the system proceeded to issue an advisory message. This message was then sent through SMS to the necessary mental health care experts, in order to facilitate the provision of necessary psychological support.

In Section II of the research paper, recent advancements in stress and emotion detection systems based on Internet of Things (IoT), machine learning, and fuzzy logic are discussed. In Section III of the paper, the designed SEDS is explained in detail. The fourth section provides an analysis of the experimental results. The fifth section finishes with a discussion of the conclusions derived from the designed system and suggestions for improvement.

## II. Related Works

Numerous research endeavors have been undertaken to assess the degrees of stress and psychological states in individuals through the examination of biological markers and facial traits. The adoption of recent advances in technology, such as the Internet of Things (IoT) [8]-[11], machine learning [10]-[12], deep learning [13],[14] and fuzzy logic [15]-[18], has been observed in the development of systems that detect stress and emotions. Each of these systems is intended to aid mental health professionals in the continuous assessment of a person's psychological status and in advising effective methods of handling stress and negative emotions in their everyday activities.

A study conducted by [9] involved the development of an emotion detection system utilizing Internet of Things (IoT) technology. This system incorporated three physiological sensors to precisely measure heart rate, body temperature, and body movement. These sensors are linked to an Arduino Nano, which processes and analyzes the data to determine whether a driver's psychological state is normal or angry. [10] developed an IoT-based smart clinical stress system by employing NodeMCU and Raspberry Pi microcontrollers that facilitate distant tracking of patients' stress levels by medical professionals. The system comprises a medical module designed to assess the galvanic skin reaction, saturation of oxygen, and cardiac rate of the patient. The module is hooked up to the patient's arm and facilitates the transmission of recorded physiological data to a Firebase server for the purposes of storing and subsequent display in mobile applications. The values are obtained and analyzed by the utilization of the Support Vector Machine (SVM) approach, which aims to identify the occurrence or absence of stress in the patient. The improvement in the research conducted by [10] was done in [11] with the addition of five machine learning algorithms, namely Logistic Regression (LR), K-Nearest Neighbors (KNN), SVM, Decision Tree (DT), and Random Forest (RF), into the stress detection system.

The research carried out by [12] involved the development of a module based on the Arduino platform. The primary objective of this module was to monitor cardiac rate using a photoplethysmography sensing component. The data obtained has been transferred over the Bluetooth module and then saved in a CSV file. Upon the retrieval of heart rate information, an SVM machine learning technique was applied to forecast stress levels and categorize emotions into positive, negative, and neutral states. [13] presented a proposed framework for the development of a deep learning system that can effectively detect emotions by analyzing facial expressions. The task encompasses the sequential steps of face recognition, feature extraction, and emotion classification. The emotions that are classified include anger, surprise, happiness, sadness, disgust, fear, and neutrality. This classification is achieved by the utilization of Convolutional Neural Networks (CNN). With the same goal of facial emotion recognition as [13], [14] developed a Raspberry Pi-based system capable of predicting emotional states using the CNN technique.

The application of fuzzy logic was employed to forecast medical health risk levels, categorized as zero, low, moderate, or high risk based on biological parameters acquired through the IoT-based telemedicine monitoring system designed by [15]. The Mandami fuzzy logic-based clinical decision support system was created in MATLAB, with rules based on the Modified National Early Warning

*International Journal on Recent and Innovation Trends in Computing and Communication*
***ISSN: 2321-8169 Volume: 11 Issue: 9***
***Article Received:*** *25 July 2023* ***Revised:*** *12 September 2023* ***Accepted:*** *30 September 2023*

Score (m-NEWS) and NEWS2. On the other hand, [16] developed a multiple input, one output fuzzy model that takes psychological variables such as SBP, BMI, and age, as well as the PHQ-9 depression test score, as input and evaluates the degree of depression as an output. A fuzzy inference-based system was created by [17] for the purpose of evaluating the level of depression, utilizing rules derived from the Beck Depression Inventory Test. The system analyzes many depression aspects, including emotional, cognitive, motivational, physical, and delusional factors, as input metrics. It then predicts the corresponding depression level, categorized as minimum, mild, moderate, or severe, as the output. [18] proposed a Fuzzy Tsukamoto AI-based system to recognize the emotional state of an e-learning user, such as relaxed, calm, anxious, or stressed. The fuzzy module's input variables will come from three sensors: GSR, Heartbeat, and temperature sensors, which will be processed by a microcontroller before being transmitted to the fuzzy system for forecasting students' psychological conditions.

In comparison to previous works [8]-[18], the presented research project involves the use of a Photon Red board microcontroller interfaced with additional sensing components such as a respiratory rate sensor, PIR motion sensor, and skin pH sensor, as well as input switches for emotional, cognitive, and behavioral stress indicators to determine an individual's stress level. Furthermore, the IoT-enabled system was linked to a machine learning-based facial emotion identification module that utilized the MIT App Inventor's Personal Image Classifier tool to detect happy, neutral, sad/upset, angry/irritable, and nervous/scared states. A fuzzy inference-based module was also integrated into the system to help predict the mental health risk as very low, low, moderate, high, or extremely high based on the physiological, cognitive, emotional, and behavioral stress parameters as fuzzy input variables.

## III. METHODS

### 1. *Block diagram of the Stress and Emotion Detection System (SEDS) integrated with a Fuzzy Inference-based Mental Health Risk Assessment Module (FIMHRAS)*

As illustrated in Fig. 1, the Photon Red board MC1 collects data on the patient's body temperature (BT), heartbeat rate (HR), oxygen saturation (SpO2), respiratory rate (RR), systolic arterial pressure (SBP), skin resistance (SR), skin pH (SkpH), and the presence of fidgeting or shaking (FS) via biosensing devices listed in Table I. In addition, MC1 receives data from a toggle switch that correlates with a person's discomfort or pain level, serving as a physical indicator of stress. The MC1 employs the National Early Warning Score (NEWS) approach, and medical specialists advise on assigning health scores to physiological data [8],[15]. Table I shows the health score for each parameter. On the other hand, the Particle Photon microcontroller MC2 receives input signals from toggle switches and the machine learning-based face emotion recognition module installed on the user's mobile phone, which correspond to indicators of emotional, behavioral, and cognitive stress symptoms. Among these symptoms are restlessness or difficulty relaxing, difficulty focusing or concentrating, impatience or intolerance, anger or irritability, sadness or distress, and a state of nervousness or fear. The stress markers used in this research are derived from the Depression, Anxiety, and Stress Scale-21 (DASS-21) questionnaire, a widely employed self-report tool intended to evaluate prevalent psychiatric conditions such as depression, anxiety, and stress [8],[20]. Table I shows the health score assigned by MC2 for each emotional, behavioral, and cognitive stress component. MC2 computes and transmits the emotion/behavior/cognitive (EBC) score to MC1. The EBC score is subsequently combined with the individual physiological health score by the MC1 to determine the total mental health risk score (MHRS) related to stress. In cases when the assessed level of mental health risk score is classified as high or extremely high, the MC1 system establishes communication with the Arduino UNO MC3, which is connected to the GSM shield. This enables the issuance of an advisory SMS to both the patient and the mental healthcare professional, facilitating the provision of essential psychological support. The patient's data and MHRS are remotely recorded and retrieved online via the Particle Cloud and ThingSpeak Cloud services. Fig. 2 depicts the prototype of the developed SEDS.

The Mandami Fuzzy Inference-based Mental Health Risk Assessment System (FIMHRAS) is designed to assist guidance counselors, psychologists, and psychiatrists in medical decision-making and treatment planning. This computer-based system incorporates 15 input variables and a single output variable to evaluate the patient's symptoms and mental health risk level (MHRL). The physiological, emotional, behavioral, and cognitive symptoms of stress are retrieved from the ThingSpeak cloud channels and imported into MATLAB. These symptoms serve as the fuzzy input variables for the rule-based mental health risk assessment system that has been developed in MATLAB. The FIMHRAS outputs the patient's MHRL, which is then uploaded to the ThingSpeak cloud platform using MATLAB. The stress related MHRL and MHRS, as well as the recommended interventions stated in Table II, are then displayed in the customized SEDS mobile application.

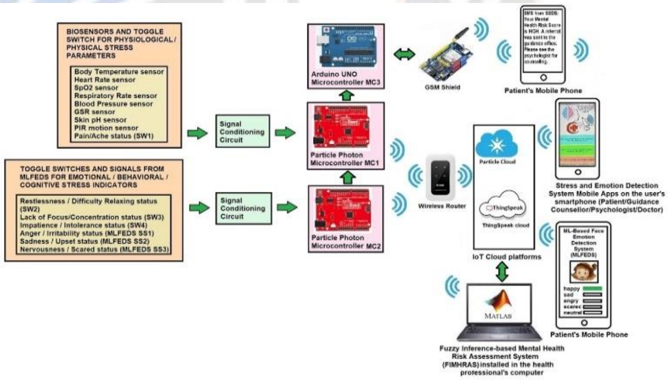


**Fig. 1.** System block diagram


**Fig. 2.** Prototype of the Stress and Emotion Detection System

**TABLE I.** Health scores for the physiological, emotional, behavioral, and cognitive stress indicators [8],[15]

| | Parameters | SEDS Input Source (Biosensor/ Switch/ MLFEDS signal) | Unit | Health Score | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | 3 | 2 | 1 | 0 | 1 | 2 | 3 |
| Physiological/Physical parameters | Body Temperature (BT) | DS18B20 Temperature sensor | °C | ≤ 35.0 | | 35.1 - 36 | 36.1 - 38 | 38.1 - 39 | ≥ 39.1 | |
| | Pulse/ Heart Rate (HR) | Sunrom1437 BP with heart rate sensor | beats per minutes (bpm) | ≤ 40.0 | | 41 - 50 | 51 - 90 | 91 - 110 | 111 - 130 | ≥ 131 |
| | Blood Oxygen Level ($SpO_2$) | MAX30100 Pulse Oximetry sensor | % | ≤ 91 | 92- 93 | 94 - 95 | 96 - 100 | | | |
| | Respiratory / Breathing Rate (RR) | MLX90614 for inhale and exhale breath temperature sensing | breaths per minute (brpm) | ≤ 8 | | 9 - 11 | 12 - 20 | | 21 -24 | ≥ 25 |
| | Systolic BP (SBP) | Sunrom1437 BP with heart rate sensor | mmHg | ≤ 90 | 91 - 100 | 101 - 110 | 111 - 140 | 141 - 219 | | ≥ 220 |
| | Pain/Ache status | Toggle switch (SW1) | Volts | | | | 0 - 0.8 | 3.3 - 5 | | |
| | Skin Resisitance (SR) | Grove Galvanic Skin Response (GSR) sensor | Ohms | | | < 60000 | ≥ 60000 | | | |
| | SkinpH (SkpH) | Skin pH sensor | - | | | <4.8 | 4.8 - 5.8 | > 5.8 | | |
| | Fidgeting/Shaking (FS) | HC-SR501 Passive Infrared sensor (PIR) for motion detection | Volts | | | | 0 - 0.8 | 3.3 - 5 | | |
| Emotional, Behavioral and Cognitive indicators | Restlessness/ Difficulty Relaxing | Toggle switch (SW2) | Volts | | | | 0 - 0.8 | 3.3 - 5 | | |
| | Lack of Focus/ Concentration | Toggle switch (SW3) | Volts | | | | 0 - 0.8 | 3.3 - 5 | | |
| | Impatience/ Intolerance | Toggle switch (SW4) | Volts | | | | 0 - 0.8 | 3.3 - 5 | | |
| | Anger/Irritability | MLFEDS Anger Status Signal (SS1) | Volts | | | | 0 - 0.8 | 3.3 - 5 | | |
| | Sadness/Being Upset | MLFEDS Sadness Status Signal (SS2) | Volts | | | | 0 - 0.8 | 3.3 - 5 | | |
| | Nervousness/ Being Scared | MLFEDS Scared Status Signal (SS3) | Volts | | | | 0 - 0.8 | 3.3 - 5 | | |

**TABLE II.** Stress-related health risk scores and levels with the corresponding mental health care recommendations [8]

| Total MHR Score due to stress | Mental Health Risk Level due to stress | Mental Health Care Recommendations |
|---|---|---|
| *0 to 3* | *Very Low Mental Health Risk (VLMHR)* | *Continue to keep a healthy mind and body. Live a healthy lifestyle.* |
| *4 to 6* | *Low Mental Health Risk (LMHR)* | *Do deep breathing, exercise and meditation. Take a rest and sleep. Eat a balanced diet. Go out with family/friends.* |
| *7 to 9* | *Medium Mental Health Risk (MMHR)* | *Do deep breathing, exercise and meditation. Take a rest and sleep. Eat a balanced diet. Go out with family/friends.* |
| *10 to 15* | *High Mental Health Risk (HMHR)* | *Please proceed to the guidance counselling center or hospital for mental health consultation. Referral was send to the mental healthcare practitioners.* |
| *>16* | *Extremely High Mental Health Risk (EHMHR)* | *Please proceed to the guidance counselling center or hospital for mental health consultation. Referral was send to the mental healthcare practitioners.* |

*International Journal on Recent and Innovation Trends in Computing and Communication*
***ISSN: 2321-8169 Volume: 11 Issue: 9***
***Article Received:** 25 July 2023 **Revised:** 12 September 2023 **Accepted:** 30 September 2023*

---

*2. Development and Implementation of the Fuzzy Inference-based Mental Health Risk Assessment System (FIMHRAS)*

Fuzzy Inference-based Mental Health Risk Assessment System (FIMHRAS) is a computer-based application that has been developed with the purpose of assisting guidance counselors and other professionals in the field of mental health in making clinical decisions and formulating treatment strategies considering the patient's stress-related indicators and MHRL. When dealing with complicated and unstable biological input data, fuzzy logic, a subset of artificial intelligence, has the capacity to replicate human deductive thinking, enabling more accurate inferences under uncertain situations [15]. The FIMHRAS has 15 inputs that correlate to physiological, emotional, behavioral, and cognitive stress indicators and only one output that corresponds to the patient's MHRL, as shown in Fig. 3. The patient's stress indicators are acquired from the ThingSpeak cloud channels and imported into MATLAB using the thingSpeakRead function. These symptoms serve as the fuzzy input variables for the MATLAB-implemented rule-based mental health risk evaluation module. The FIMHRAS produces the MHRL of the patient as an output, which is subsequently transmitted to the ThingSpeak cloud platform utilizing MATLAB's thingSpeakWrite function.

Table III displays the fuzzy sets and corresponding ranges for each input variable, as recommended by mental healthcare practitioners and specified in the DASS-21 and NEWS assessments. The membership functions of fuzzy sets were considered to be in the shape of a trapezoid. The determination of the severity of a patient's psychological condition is dependent upon the selection of one out of a total of 23 potential MHRL categories. Table IV displays the output variable of the FI-MDSS, together with its associated fuzzy sets and their respective ranges. The membership functions for health risk categories were configured in a triangular form.

The FIMHRAS rule base engine is made up of 62,208 IF-THEN rules that are designed to deal with a wide variety of potential mental health concerns related to stress. The rules were established based on guidance provided by mental health professionals, as well as utilizing the NEWS and DASS-21 scoring methods. Because of the dependency of the physiological and psychological inputs, the logical AND operation was used in the rules. The defuzzification process involves utilizing a fuzzy centroid technique to obtain a precise result from the data. Fig. 4 illustrates a sample fuzzy rule that is utilized to determine the level of mental health risk for an individual.

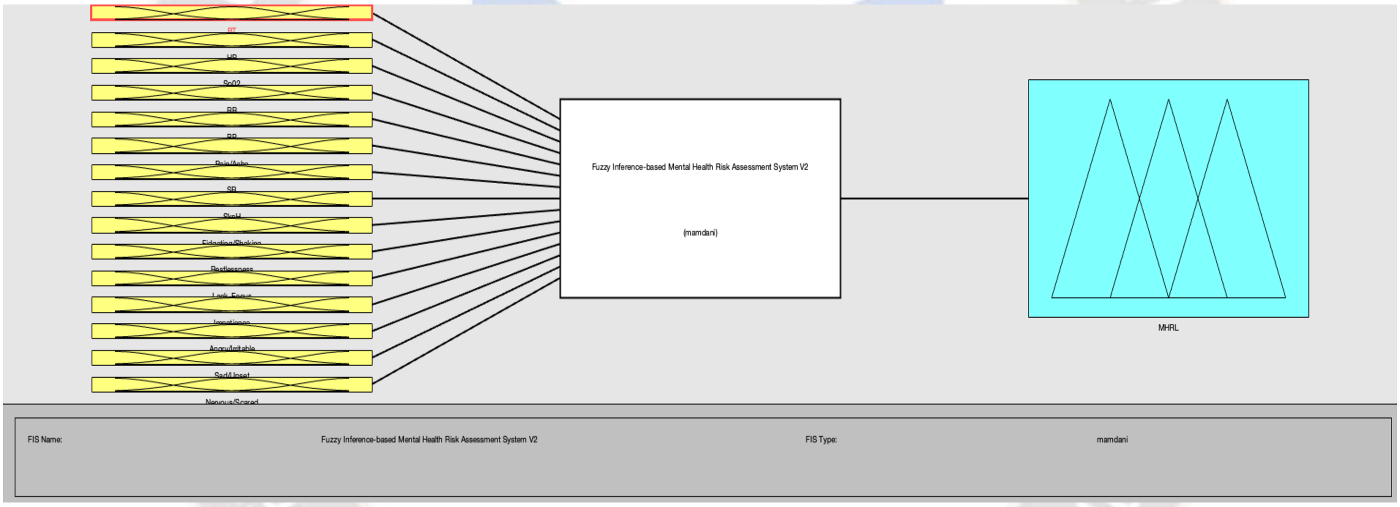


**Figure 3.** FIMHRAS implementation

**TABLE III.** FIMHRAS fuzzy sets and corresponding ranges for each input variable

| FIMHRAS Input Field (Physiological, Emotional Behavioral and Cognitive Parameters) | | Fuzzy Sets | Range | Unit |
|---|---|---|---|---|
| | Body Temperature (BT) | NRM_ElevBT_0 | 35.9 ≤ BT ≤ 37.4 | °C |
| | | | 37.1 ≤ BT ≤ 38.2 | |
| | | HighBT_1 | 37.9 ≤ BT ≤ 39.2 | |
| | | VHighBT_2 | BT ≥ 38.9 | |
| | | LowBT_1 | 34.9 ≤ BT ≤ 36.2 | |
| | | VLowBT_3 | BT ≤ 35.0 | |
| | Pulse/ Heart Rate (HR) | NormHR_0 | 49 ≤ HR ≤ 92 | bpm |
| | | LowHR_1 | 39 ≤ HR ≤ 52 | |
| | | VLowHR_3 | HR ≤ 40 | |
| | | ModHighHR_1 | 89 ≤ HR ≤ 112 | |
| | | HighHR_2 | 109 ≤ HR ≤ 132 | |
| | | VHighHR_3 | HR ≥ 131 | |

| | | | | |
|---|---|---|---|---|
| Physiological/Physical parameters | Blood Oxygen Level (SpO2) | NRMSp02_0 | $95 \le SpO2 \le 100$ | % |
| | | ModLSp02_1 | $93 \le SpO2 \le 96$ | |
| | | LowSp02_2 | $91 \le SpO2 \le 94$ | |
| | | VLowSp02_3 | $SpO2 \le 91$ | |
| | Respiratory / Breathing Rate (RR) | NRM_RR_0 | $11 \le RR \le 21$ | brpm |
| | | HighRR_2 | $20 \le RR \le 26$ | |
| | | VHighRR_3 | $RR \ge 25$ | |
| | | LowRR_1 | $7 \le RR \le 12$ | |
| | | VLowRR_3 | $RR \le 8$ | |
| | Systolic BP (SBP) | VLowSBP_3 | $SBP \le 90$ | mmHg |
| | | LowSBP_2 | $89 \le SBP \le 102$ | |
| | | ModLSBP_1 | $99 \le SBP \le 112$ | |
| | | SBP_0 | $109 \le SBP \le 141$ | |
| | | highSBP_1 | $139 \le SBP \le 221$ | |
| | | VhighSBP_3 | $SBP \ge 220$ | |
| | Pain/Ache status | PA_0 | 0 to 2 | Volts |
| | | PA_3 | 1.9 to 5 | |
| | Skin Resisitance (SR) | NRMSR_0 | $SR \ge 60K$ | Ohms |
| | | LowSR_1 | $SR \le 61K$ | |
| | SkinpH (SkpH) | NRMpH_0 | $4.7 \le SkpH \le 5.9$ | - |
| | | LowpH_1 | $SkpH \le 4.8$ | |
| | | HighpH_1 | $SkpH \ge 5.8$ | |
| | Fidgeting/Shaking (FS) | FS_0 | 0 to 2 | Volts |
| | | FS_1 | 1.9 to 5 | |
| Emotional, Behavioral and Cognitive indicators | Restlessness/ Difficulty Relaxing | Restless_0 | 0 to 2 | Volts |
| | | Restless_1 | 1.9 to 5 | |
| | Lack of Focus/ Concentration | LackFocus_0 | 0 to 2 | Volts |
| | | LackFocus_1 | 1.9 to 5 | |
| | Impatience/ Intolerance | Impatient_0 | 0 to 2 | Volts |
| | | Impatient_1 | 1.9 to 5 | |
| | Anger/Irritability | Angry_0 | 0 to 2 | Volts |
| | | Angry_1 | 1.9 to 5 | |
| | Sadness/Being Upset | Sad_0 | 0 to 2 | Volts |
| | | Sad_1 | 1.9 to 5 | |
| | Nervousness/ Being Scared | Nervous_0 | 0 to 2 | Volts |
| | | Nervous_1 | 1.9 to 5 | |

**TABLE IV.** FIMHRAS fuzzy sets and corresponding ranges for the output variable

| FIMHRAS Output Field | Fuzzy Sets | Range |
|---|---|---|
| Mental Health Risk Level (MHRL) | VLMHR0 | $0.0 < MHRL < 0.5$ |
| | VLMHR1 | $0.5 < MHRL < 1.5$ |
| | VLMHR2 | $1.5 < MHRL < 2.5$ |
| | VLMHR3 | $2.5 < MHRL < 3.5$ |
| | LMHR4 | $3.5 < MHRL < 4.5$ |
| | LMHR5 | $4.5 < MHRL < 5.5$ |
| | LMHR6 | $5.5 < MHRL < 6.5$ |
| | MMHR7 | $6.5 < MHRL < 7.5$ |
| | MMHR8 | $7.5 < MHRL < 8.5$ |
| | MMHR9 | $8.5 < MHRL < 9.5$ |
| | HMHR10 | $9.5 < MHRL < 10.5$ |
| | HMHR11 | $10.5 < MHRL < 11.5$ |
| | HMHR12 | $11.5 < MHRL < 12.5$ |
| | HMHR13 | $12.5 < MHRL < 13.5$ |
| | HMHR14 | $13.5 < MHRL < 14.5$ |
| | HMHR15 | $14.5 < MHRL < 15.5$ |
| | EHMHR16 | $15.5 < MHRL < 16.5$ |
| | EHMHR17 | $16.5 < MHRL < 17.5$ |
| | EHMHR18 | $17.5 < MHRL < 18.5$ |
| | EHMHR19 | $18.5 < MHRL < 19.5$ |
| | EHMHR20 | $19.5 < MHRL < 20.5$ |
| | EHMHR21 | $20.5 < MHRL < 21.5$ |
| | EHMHR22 | $21.5 < MHRL < 22.5$ |
| | EHMHR23 | $22.5 < MHRL < 23.5$ |

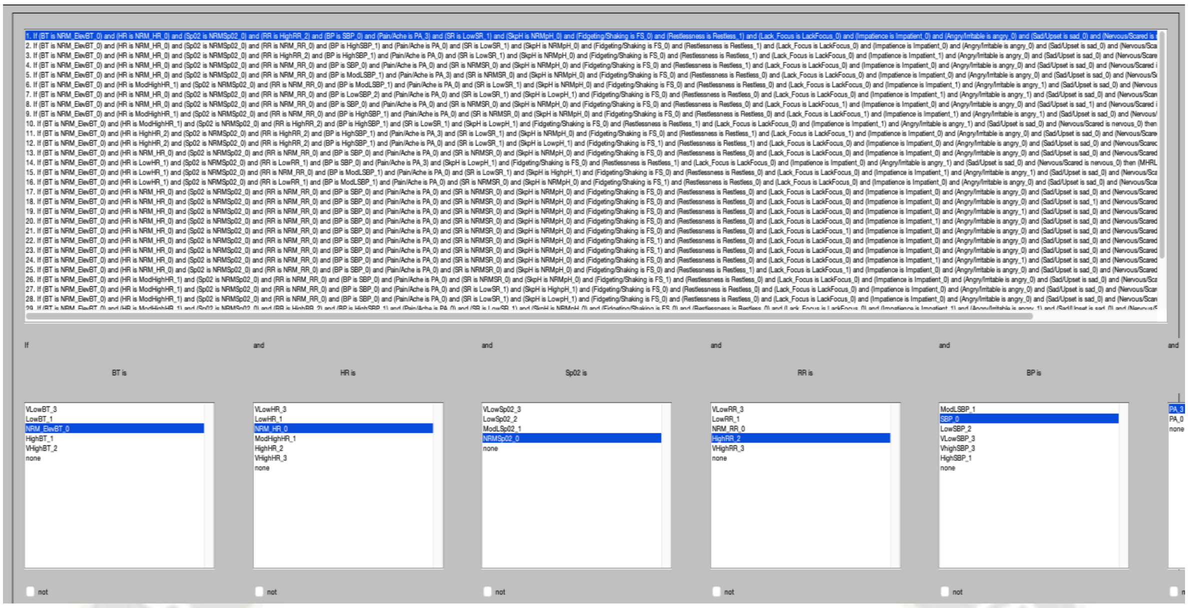

**Fig. 4.** Sample fuzzy rules of the FIMHRAS

*3. Machine Learning-based Face Emotion Detection System (MLFEDS)*

The machine learning-based emotion detection system seen in Fig. 5 was developed using MIT App Inventor's Personal Image Classifier tool. The application uses artificial intelligence to recognize and classify human emotions by tracking facial expressions. The basic purpose of MLFEDS is to identify and characterize five distinct emotional states: happiness, sadness, anger, nervousness, and neutrality. The created MLFEDS is compatible with Android phones and enables real-time emotional analysis via the camera.

To aid with the training process, a dataset of 200 captured photos for each of the five different emotional states is gathered. During the training phase, the system employs a machine learning algorithm to recognize complicated patterns and features in the images that are related to various emotional states. The patterns include the curve of the mouth, brow position, eye apertures, and the level of activity displayed by facial muscles. Throughout training, the model's internal parameters are continuously adjusted, improving its ability to identify diverse emotions, and obtaining better levels of accuracy.

Confidence levels for each emotion are continuously assessed in the design of the MLFEDS (Multi-Level Facial Emotion Detection System). When the confidence level for the angry face condition exceeds 50%, a logic-1 signal with a voltage of 3.3 V is sent to field 6 on the ThingSpeak channel. This signal is used to determine whether the individual is experiencing a state of anger or agitation. Similarly, when the confidence level for the sad face condition crosses 50%, a logic-1 signal with a voltage of 3.3 V is delivered to field 7, indicating the individual's sadness or upset feeling. Moreover, once the confidence level for the nervous face condition becomes greater than 50%, a logic-1 signal with a value of 3.3 V is communicated to field 8. This signal indicates whether the individual is feeling nervous or scared. However, in cases where the confidence level for the happy or neutral state is above 50%, logic-0 signals are transmitted to fields 6, 7, and 8 on the ThingSpeak channel, with a voltage of 0 V, as depicted in Fig. 5.


**Fig. 5.** Machine learning-based Face Emotion Detection System (MLFEDS) installed in an Android mobile phone

## IV. DATA AND ANALYSIS OF RESULTS

### *A. Results of the IoT-based Stress and Emotion Detection System (SEDS)*

The testing of the developed SEDS involved the participation of thirty volunteers, consisting of twelve students, twelve teaching staff, and one non-teaching staff from UTAS-Al Musanna in Oman, as well as five students from universities in Manila, Philippines. These individuals voluntarily participated in the testing process. The primary aim of the research work was to evaluate the stress scores and ascertain the levels of mental health risk linked to stress among individuals within an academic institution. The experiment was carried out over a period of seven consecutive days, consisting of two sessions each day. These sessions were done both before and during the participants' regular study or work hours. To provide a comparative analysis with the data collected from the SEDS prototype, participants were also requested to complete the DASS-21 questionnaire for a stress assessment. Figs. 6 and 7 depict experimental results pertaining to the physiological, emotional, behavioral, and cognitive symptoms exhibited by an individual participant in response to stress experienced during working hours. These data were acquired through the utilization of the designed system and were accessed through smartphone applications and the ThingSpeak cloud platform. The results were obtained using a non-invasive method that ensures the safety of the participants. The sample average stress-related mental health risk scores and levels obtained using the SEDS prototype are presented in Table V. The resulting mental health risk levels were then compared with the DASS-21 questionnaire results to determine the system's accuracy.

According to research results shown in Table V, it was observed that individuals experienced a rise in their body thermal parameters ranging from 0.1 to 0.3 °C when subjected to stressful situations either in an educational setting or in a professional environment. This phenomenon pertains to the secretion of stress hormones, namely cortisol, which has the potential to elevate both metabolic rate and body temperature [21], [22]. When the participants experienced stress, there was a significant rise in their systolic arterial pressure, heartbeat rate, and breathing rate. The physiological response to stress involves the production of chemicals, including adrenaline and cortisol, which stimulate various effects on the body. These effects include an increase in heart rate, accelerated respiration, and constriction of blood vessels, ultimately leading to an elevation in blood pressure [23]. The respondents' blood oxygen levels exhibited a decrease ranging from 1% to 2% in response to stress. The physiological response to stress can affect the distribution and utilization of oxygen in various bodily tissues, as indicated by the measurement of SpO2. From Table V, it has been observed that the skin resistance of individuals tends to decrease when exposed to stressors during working hours or attending classes. The initiation of the sympathetic nervous system during periods of stress leads to increased sweat gland activity in the skin. As a result, the skin exhibits an increased electrical conductivity, leading to a reduction in its resistance [22]. Based on the pH data presented in Table V, it was observed that the skin acidity or alkalinity levels of five respondents exhibited deviations from the specified normal range when subjected to stressors. Stress hormones have the ability to increase sebum production, which causes a pH imbalance [24]. When the pH of the skin exceeds its optimal range, resulting in alkalinity, it can compromise the integrity of the skin's protective barrier [24], [25]. Subsequently, this can cause the skin more susceptible to infections, dryness, and many dermatological conditions. On the contrary, in the event that the pH level falls below the established range, it results in increased acidity which can lead to various adverse effects such as irritation, redness, and a high susceptibility to skin conditions such as acne. This is attributed to the acidic environment facilitating the proliferation of specific harmful bacteria [24], [25].

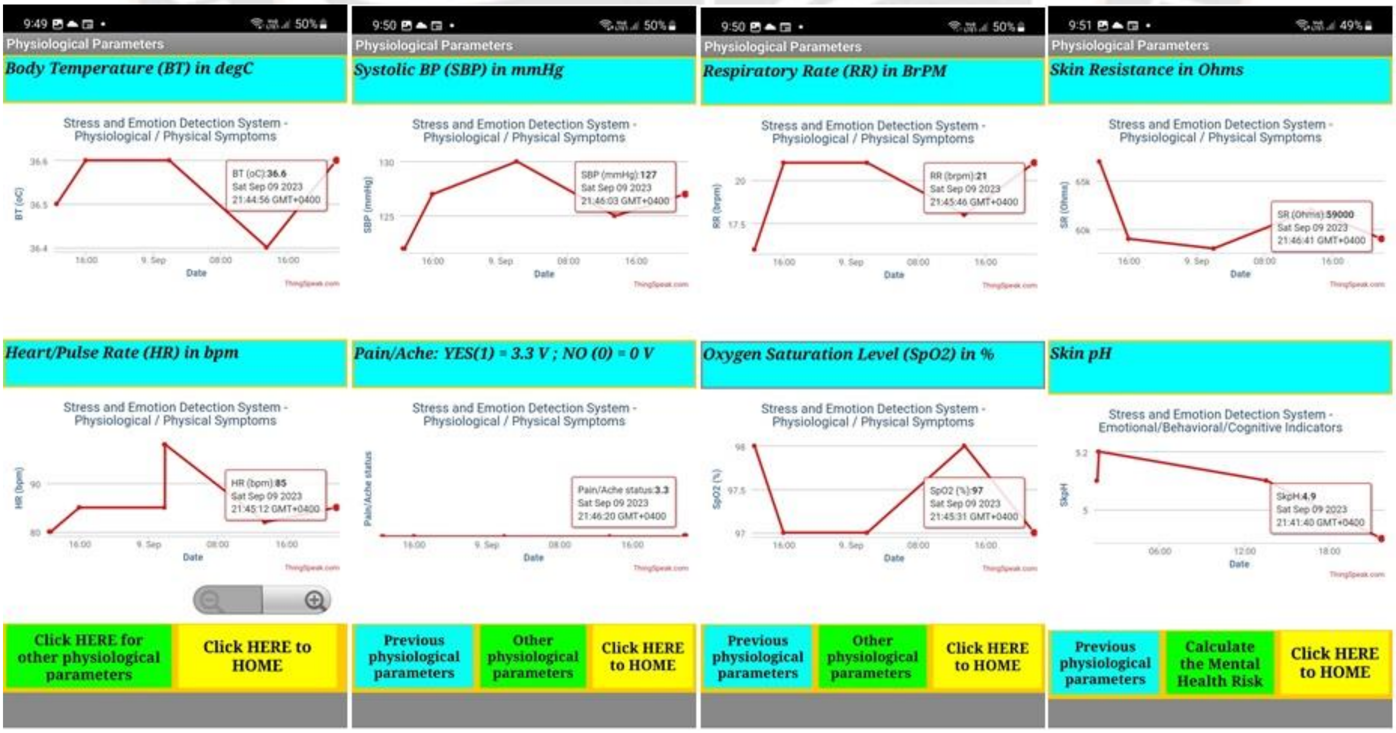


**Fig. 6.** Physiological and physical parameters of respondent RN1 as seen in the dedicated SEDS mobile app and ThingSpeak cloud


**Fig. 7.** Emotional, behavioral, and cognitive stress indicators of respondent RN1 as seen in the dedicated SEDS mobile app and ThingSpeak cloud

**Table 5.** Sample average results obtained from the SEDS prototype

| RN | Physiological Parameters | | | | | | | | | | | | | | Emotional, Behavioral, Cognitive and Physical Symptoms of Stress | | | | | | | | Mental Health Score and Risk Level due to Stress | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Before work or class hours | | | | | | | During working hours or class hours | | | | | | | | | | | | | | | | | | | |
| | BT | SBP | HR | SpO2 | RR | SR | SkpH | BT | SBP | HR | SpO2 | RR | SR | SkpH | Restlessness/ Difficulty relaxing | Lack of Focus/ Concentration | Impatient/ Intolerant | Anger/ Irriability | Sadness/ Upset | Nervous/Scared | Pain / Ache (Headache, Stomach ache, Bodyache) | Fidgeting/ Shaking | SEDS MHRS | FIMHRAS output | FIMHRAS MHRL | DASS-21 Stress Score | DASS-21 Stress Level |
| 1 | 36.5 | 122 | 80 | 98 | 16 | 65K | 5.2 | 36.6 | 127 | 85 | 97 | 21 | 59K | 4.9 | Y | N | N | N | N | Y | Y | N | 8 | 8.02 | Moderate | 10 | Moderate |
| 2 | 36.5 | 136 | 78 | 98 | 16 | 62K | 5.3 | 36.7 | 142 | 82 | 97 | 18 | 52K | 5.4 | Y | N | N | N | N | N | Y | N | 6 | 6.00 | Low | 8 | Mild |
| 3 | 36.3 | 146 | 70 | 99 | 18 | 61K | 6.4 | 36.5 | 159 | 90 | 98 | 21 | 50K | 6.4 | Y | N | Y | Y | N | N | N | N | 8 | 8.02 | Moderate | 11 | Moderate |
| 4 | 36.4 | 135 | 81 | 99 | 16 | 72K | 5.7 | 36.4 | 138 | 88 | 98 | 18 | 65K | 5.9 | N | Y | N | N | Y | N | N | N | 3 | 2.94 | Very Low | 3 | Normal |
| 5 | 36.1 | 105 | 71 | 98 | 16 | 67K | 4.9 | 36.2 | 108 | 76 | 97 | 20 | 61K | 4.7 | Y | Y | N | N | N | Y | N | N | 5 | 5.04 | Low | 9 | Mild |
| 6 | 36.3 | 139 | 86 | 99 | 18 | 64K | 6.3 | 36.6 | 148 | 92 | 98 | 22 | 58K | 6.5 | Y | Y | Y | Y | N | N | N | N | 10 | 10.00 | HIgh | 12 | Moderate |
| 7 | 36.0 | 112 | 76 | 98 | 14 | 69K | 5.4 | 36.1 | 115 | 82 | 98 | 18 | 57K | 5.5 | N | N | N | N | Y | N | N | N | 2 | 2.03 | Very Low | 4 | Normal |
| 8 | 36.2 | 90 | 73 | 99 | 14 | 63K | 6.1 | 36.4 | 98 | 80 | 98 | 16 | 53K | 6.3 | N | N | Y | Y | N | N | Y | N | 9 | 9.02 | Moderate | 10 | Moderate |

Based on Table V and Fig. 6, respondent RN1 had a BT of 36.6ºC, an HR of 85 bpm, a SpO2 of 97%, an SBP of 127 mmHg, and a pH level of 4.9, all of which were assigned a health score of 0. RN1 had an RR of 21 brpm, which corresponded to a health score of 2, an SR of 59000 Ohms, which corresponded to a health score of 1, and a headache during testing, which resulted in a health score of 3 for pain/ache condition. According to Table V and Fig. 7, RN1 did not experience fidgeting, lack of focus, feelings of impatience, sadness, or anger during testing, but felt restless and nervous, yielding an EBC score of 2. When all of the health scores were combined together, the total MHRS was 8, corresponding to a mental health risk level of moderate. This MHRL level matched the level of stress indicated by the DASS-21 assessment. Participants RN4 and RN7 demonstrated a very low mental health risk level, which corresponded to a stress level categorized as normal based on the DASS-21 test. Participants RN2 and RN5 demonstrated a low degree of mental health risk, corresponding to mild stress levels as determined by the DASS-21.

The experimental results demonstrated that the SEDS and FIMHRAS evaluations exhibit an increased level of accuracy in assessing the risk of mental health when compared to the [8]. Specifically, 90% accuracy was achieved since the stress-related mental health risk levels of 27 out of 30 participants closely correlated to the stress levels determined by the DASS-21 assessment tool. However, there were only slight differences noted in three separate cases, which could be attributed to borderline conditions and the subjective nature of the responses provided by participants while filling out the DASS-21 questionnaire. In the case of respondent RN6, the calculated DASS-21 score is 12, indicating a moderate level of stress. On the other hand, the developed system assigned a mental health risk score of 10 to the individual, suggesting a high risk of mental health issues arising from stress. This finding demonstrates the ability of the developed system to anticipate potential rises in stress levels. The referral message sent to the mental health care professional for high MHRL is shown in Fig. 8.

---

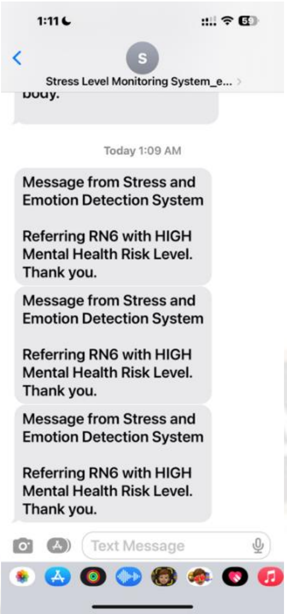


**Fig. 8.** SMS sent to the mental health professional referring a patient with high mental health risk

### B. *Results of the Fuzzy Inference-based Mental Health Risk Assessment System (FIMHRAS)*

The experimental data collected from RN1 as seen in Figs. 6 and 7 were exported from the ThingSpeak cloud and imported to MATLAB. The acquired parameters were processed and analyzed by the FIMHRAS based on the fuzzy rule #1 as shown in Fig. 9, generating an output of 8.02 which corresponded to a moderate mental health risk. This result was exported to the ThingSpeak channel and displayed in the mobile app as seen in Fig. 10. The MHRL due to stress assessment from the designed system matched the DASS-21 stress level result presented in Table V.

**Fig.9** Sample FIHMRAS output based on rule#1


**Figure 10.** The MHRS and MHRL displayed on the customized mobile app with the suggested stress management action

### C. *Results of the Machine Learning-based Face Emotion Detection System (MLFEDS)*

The facial emotion detection system, which relies on machine learning, was subjected to a series of tests. Each emotion was tested 30 times, resulting in 130 successful detections out of a total of 150 trials. This corresponded to an accuracy rate of 86.67%. The system correctly identified 28 out of 30 happy faces, 27 out of 30 angry faces, 25 out of 30 sad faces, 25 out of 30 worried faces, and 25 out of 30 neutral expressions. Several factors contributed to inaccuracies in emotion recognition, including variations in facial characteristics among individuals, fluctuations in lighting conditions, variations in the intensity of emotional facial expressions, and the size of the training data set. Fig. 11 displays the sample output of the MLFEDS program in accurately detecting emotions of sadness and anger.

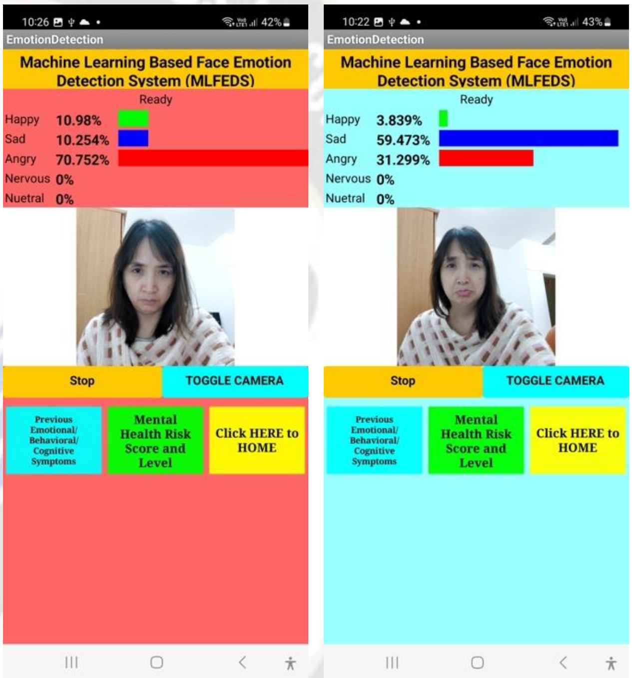


**Fig. 11.** Sample output of the MLFEDS

## V. CONCLUSION

In conclusion, the Stress and Emotion Detection System (SEDS) is an innovative approach that integrates the Internet of Medical Things (IoMT), machine learning, and fuzzy logic technologies for the purpose of mental health monitoring and management. SEDS provides an in-depth understanding of a person's psychological and physiological well-being through the utilization of IoT-enabled Photon Red boards. The microcontrollers PPI and PP2 were used to gather and analyze data from non-invasive biomedical sensors, emotional, behavioral, and cognitive symptom switch indicators, and facial recognition systems. The combined usage of Internet of Things (IoT) cloud services and mobile applications ensures easy access to user data, consequently promoting increased mental health awareness and involvement.

A significant feature of the developed prototype is its capacity to evaluate the risk of stress-related mental health issues by employing fuzzy logic and effectively categorizing stress-related psychological health hazards with a high degree of accuracy. SEDS has the potential to revolutionize mental health treatment by offering personalized stress management suggestions and facilitating prompt interventions through automated referrals to mental health specialists. Furthermore, the system's effectiveness in recognizing and evaluating mental health risks related to stress is supported by its accuracy rates of 90% when compared to the DASS21 stress scale and an 86.67% classification accuracy for emotion detection. As the importance of mental health is recognized globally, the SEDS integrated with FIMHRAS illustrates an innovative approach to promoting well-being, presenting viable solutions for improving mental health and enhancing persons' quality of life.

In order to improve the operation and overall efficiency of the designed system, several modifications can be implemented. Firstly, the inclusion of additional biosensors to detect muscle activity, brain activity, and blood sugar level would provide a more thorough assessment of how stress affects a person’s physiological and psychological well-being. Secondly, the integration of various artificial intelligence techniques into the system's stress scoring and mental health risk assessment processes would enhance the system's decision-making capabilities. Thirdly, it is recommended to assess the reliability of the system by conducting a comparative analysis between the outcomes generated by the SEDS and other established stress test standards. Lastly, the incorporation of depression and anxiety monitoring within the system would further enhance its functionality.

## ACKNOWLEDGMENT

The authors would like to thank the UTAS - Al Musanna for their continued assistance of this research work, as well as the Oman Research Council (TRC) for providing the necessary funding. We would like to thank the student research assistants, as well as the students and staff members who volunteered to participate in the research's testing phase. Guidance counselors, psychologists, psychometricians, and other healthcare professionals are acknowledged for their participation in interviews, guidance, and valuable input on the project.

## REFERENCES

[1] Adom, Dickson, Joshua Chukwuere, and Mavis Osei. "Academic Stress among Faculty and Students in Higher Institutions." *Pertanika Journal of Social Sciences & Humanities* 28, no. 2 (2020).

[2] Kavita, Kumari, and Norliza Che Hassan. "Work stress among teachers: A comparison between primary and secondary school teachers." *International Journal of Academic Research in Progressive Education and Development* 7, no. 4 (2018): 60-66.

[3] Collie, Rebecca J., Jennifer D. Shapka, and Nancy E. Perry. "School climate and social–emotional learning: Predicting teacher stress, job satisfaction, and teaching efficacy." *Journal of educational psychology* 104, no. 4 (2012): 1189.

[4] Peltzer, Karl, Olive Shisana, Khangelani Zuma, Brian Van Wyk, and Nompumelelo Zungu-Dirwayi. "Job stress, job satisfaction and stress-related illnesses among South African educators." *Stress and Health: Journal of the International Society for the Investigation of Stress* 25, no. 3 (2009): 247-257.

[5] Murff, Sharon Hall. "The impact of stress on academic success in college students." *ABNF JOURNAL* 16, no. 5 (2005): 102.

[6] Malik, Mustafa, and Sarfaraz Javed. "Perceived stress among university students in Oman during COVID-19-induced e-learning." *Middle East Current Psychiatry* 28, no. 1 (2021): 49.

[7] Pascoe, Michaela C., Sarah E. Hetrick, and Alexandra G. Parker. "The impact of stress on students in secondary school and higher education." *International journal of adolescence and youth* 25, no. 1 (2020): 104-112.

[8] Nagayo, Analene M., Mahmood Z. Al Ajmi, Naga R. K. Venkatta, Fatma Al Buraidi. “Monitoring Stress Level and Related Health Risks Using IoT to Raise Mental Health Awareness in Academic Institutions.” In *Proceedings of International Conference on Development on Education Research, Information Systems and Management:* ICDRISM 2023. Dubai: IFERP India, 2023

[9] Kaur, Jasleen, Neera Batra, and Sonali Goyal. "SmartEmoDetect: An IoT Based Emotion Monitoring Wearable Technology for Drivers." *J. Comput. Theor. Nanosci* 16 (2019): 1-5.

[10] Hadhri, Sami, Mondher Hadiji, and Walid Labidi. "An intelligent stress detection and monitoring system using the IoT environment." In 2022 International Conference on Technology Innovations for Healthcare (ICTIH), pp. 20-25. IEEE, 2022.

[11] Hadhri, Sami, Mondher Hadiji, and Walid Labidi. "Machine Learning and IoT for Stress Detection and Monitoring." In International Conference on Computational Collective Intelligence, pp. 542-553. Cham: Springer International Publishing, 2022.

[12] Asha, Nur E. Jannat, and Riasat Khan. "Low-cost heart rate sensor and mental stress detection using machine learning." In 2021 5th International Conference on Trends in Electronics and Informatics (ICOEI), pp. 1369-1374. IEEE, 2021.

[13] Jaiswal, Akriti, A. Krishnama Raju, and Suman Deb. "Facial emotion detection using deep learning." In 2020 international conference for emerging technology (INCET), pp. 1-5. IEEE, 2020.

[14] Zahara, Lutfiah, Purnawarman Musa, Eri Prasetyo Wibowo, Irwan Karim, and Saiful Bahri Musa. "The facial emotion recognition (FER-2013) dataset for prediction system of micro-expressions face using the convolutional neural network (CNN) algorithm based Raspberry Pi." In 2020 Fifth international conference on informatics and computing (ICIC), pp. 1-9. IEEE, 2020.

[15] Nagayo, Analene Montesines, Mahmood Zayid K. Al Ajmi, Naga Rama K. Guduri, and Fatma Saleh H. AlBuradai. "IoT-based telemedicine health monitoring system with a fuzzy inference-based medical decision support module for clinical risk evaluation." In Proceedings of Third International Conference on Advances in Computer Engineering and Communication Systems: ICACECS 2022, pp. 313-336. Singapore: Springer Nature Singapore, 2023.

[16] Ekong, Victor E., Uyinomen O. Ekong, Enobakhare E. Uwadiae, Festus Abasiubong, and Emmanuel A. Onibere. "A fuzzy inference system for predicting depression risk levels." *African Journal of mathematics and computer Science Research* 6, no. 10 (2013): 197-204.

[17] Ariyanti, Retno Dina, Sri Kusumadewi, and Irving Vitra Paputungan. "Beck depression inventory test assessment using fuzzy inference system." In 2010 International Conference on Intelligent Systems, Modelling and Simulation, pp. 6-9. IEEE, 2010.

[18] Pradana, F., F. A. Bachtiar, and E. R. Widasari. "Fuzzy Tsukamoto Implementation to Detect Physiological Condition on IoT-Based e-Learning Users." International Journal of Information and Education Technology 12, no. 7

(2022): 663-667.

[19] Attia, Merna, Fatma A. Ibrahim, Mohamed Abd-Elfatah Elsady, Mohamed Khaled Khorkhash, Marwa Abdelazim Rizk, Jaffer Shah, and Samar A. Amer. "Cognitive, emotional, physical, and behavioral stress-related symptoms and coping strategies among university students during the third wave of COVID-19 pandemic." Frontiers in psychiatry 13 (2022): 933981.

[20] Lovibond, P. F., and S. H. Lovibond. "Depression Anxiety and Stress Scales." Behaviour Research and Therapy (1996).

[21] Vinkers, Christiaan H., Renske Penning, Juliane Hellhammer, Joris C. Verster, John HGM Klaessens, Berend Olivier, and Cor J. Kalkman. "The effect of stress on core and peripheral body temperature in humans." Stress 16, no. 5 (2013): 520-530.

[22] Baker, Lawrence M., and William M. Taylor. "The relationship under stress between changes in skin temperature, electrical skin resistance, and pulse rate." Journal of experimental psychology 48, no. 5 (1954): 361.

[23] Joshi, Anurag, Ravi Kiran, Harish Kumar Singla, and Ash Narayan Sah. "Stress management through regulation of blood pressure among college students." Work 54, no. 3 (2016): 745-752.

[24] Morvan, Pierre-Yves, Romuald Vallee, and M. Py. "Evaluation of the effects of stressful life on human skin microbiota." *Appl. Microbiol. Open Access* 4, no. 8 (2018).

[25] Proksch, Ehrhardt. "pH in nature, humans and skin." *The Journal of dermatology* 45, no. 9 (2018): 1044-1052.