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Stress Level Prediction and Management Using Machine Learning Techniques

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***Abstract* - A smart solution for users to classify stress levels and make predictions using Machine Learning techniques like voice and face recognition is presented in this paper. Excessive stress, which can have detrimental effects even if certain reactions can be controlled, is a common aspect of life, causing physical, mental, and emotional strain when personal and social resources are exceeded. Stress is experienced by over 100 million Americans, and in Sri Lanka, a South Asian nation, there is less emphasis on mental health than in Western and European nations. According to the World Health Organization, it is estimated that 5% to 10% of Sri Lanka's population needs treatment for mental health issues. User sentiments are anticipated, and suggestions are provided based on AI methods, utilizing the system's ability to recognize voices and faces. Additionally, cardiac and sleep issues are identified and addressed using physical body data from IoT devices. Performance in stress management software is improved by the system, which is designed to work with multiple languages. Availability in both English and Sinhala languages is ensured by the system.**

Keywords: stress, treatments, machine-learning, internet of things.

I. INTRODUCTION

Stress can be triggered by either an unavoidable occurrence or by any thought. The physical, mental, or emotional reactions that a person experiences are led by the body's response to each change it undergoes. According to statistics from the American Psychological Association (APA) from 2012, stress impacts more than 100 million Americans. In terms of mental health focus, Sri Lanka, as a South Asian country, places less emphasis on it compared to Western and European nations. According to the World Health Organization (WHO), mental health problems requiring medical attention affect 5% to 10% of Sri Lanka's population. When examining Sri Lanka, the University of Kelaniya (Sri Lanka) conducted research [1] revealing various types of stress in Sri Lanka, including Academic stress (Stress level: 61.81), Finance and economic stress (Stress level: 72.55), relationship stress (Stress level: 74.74), career growth stress (Stress level: 68.93), and physiological stress (Stress level: 73.40) [1].

Based on the results depicted in this description, relationship stress and psychological stress can be considered the predominant stress types in Sri Lanka. The English language poses an issue for many traditional Sri Lankan people when it comes to understanding technology. As a result, it is highly probable that applications or software will not be utilized by them to seek assistance in finding their health solutions. A smart mental health solution with automated tools for detecting and classifying stress levels and emotions has been recognized as an important technique that is supported by users worldwide. Digital tools such as AI integration, training deep learning models, and Convolutional Neural networks (CNN) offer an optimal solution for identifying and predicting stress levels and emotions. The traditional manual observation method is time-consuming and prone to errors, as stress and other mental illnesses are often not detected by doctors or therapists at the initial stage or at the right time.

To address these gaps, the effectiveness of various machine learning models in predicting stress levels and emotions using different datasets is investigated in this research paper. Key features that significantly contribute to stress prediction are identified. The findings of this study can assist in the development of personalized stress management interventions tailored to individual needs, ultimately improving health outcomes. To achieve this, face and voice detection technologies are proposed, along with machine learning concepts. By utilizing these features, the system is capable of identifying measurements related to the user's stress and facial emotions. Through an AI feedback system, the proposed smart solution can provide direct feedback to the user regarding their emotions and stress situation. The system utilizes IoT device-based data to obtain physical body data

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such as heart rate, blood oxygen rate, body temperature, voice decimal rate, etc. This information allows the system to monitor the user's physical body and combine it with their mental state. As a result, the system can provide comprehensive details about the user's mental state and stress level. Multiple languages can be utilized with the system to mitigate language fluency issues. To fulfill this requirement, the proposed system has been developed in English and Sinhala, which can be utilized by traditional Sri Lankan individuals to overcome their technical literacy issues.

II. BACKGROUND AND LITERATURE

Every day, people communicate with one another through their looks and gestures, which are frequently utilized effortlessly by them. These hand movements or looks on their faces are frequently made by them without even being aware of them. Inadvertent information is the main non-invasive method through which the transmitter's emotions can be ascertained. Several facial expressions that convey the same message consistently exist. It was agreed by everyone that there is a connection between emotions and moods, according to the case studies that were conducted by the researchers. Stress may show up in speech, gestures, and even facial expressions similar to other emotions and moods. Methods such as body temperature monitoring, heart rate monitoring, and blood oxygen rate monitoring are being used to help find out mental situations such as stress levels.

- A real-time application in which facial emotion can be detected in a live video stream was created by Anjali R., J. Babitha, et al. The Haarcascade technique was used to detect faces in each frame of the webcam. Machine learning and deep learning algorithms were used by them for face detection and stress detection [2]. The main components of their research, including detecting a user's face, emotion detection through face recognition, and calculating stress level using emotion recognition, were considered. Development was carried out using image processing and machine learning techniques.
- The project titled "An Android-Based Heart Monitoring System for the Elderly and for Patients with Heart Disease" was developed in 2014 by the team composed of Paola Pierleoni, Luca Pernini, et al. Key goals of their effort included accurately identifying cardiac abnormalities, monitoring heart function, and preventing heart disease, especially in the elderly and those with existing heart conditions. A complete and user-friendly system was wanted by the team that might enhance the well-being of the elderly and patients with cardiac diseases by utilizing mobile technology and adding features like stress testing, illness prevention, and precise diagnosis.[5]
- Research about the relationship between stress and sleeping habits was conducted by Laavanya Rachakonda, Anand K. Bapatla, et al. The Smart- Yoga Pillow (SaYoPillow), which is recommended as an innovative item to help comprehend the link between stress and sleep, completely materializes the idea of "Smart-Sleeping". The Smart-Yoga Pillow (SaYoPillow), which is recommended as an innovative item to help comprehend the link between stress and sleep, completely materializes the idea of "Smart-Sleeping". The average physiological changes and stress data are integrated and safely delivered to the IoT cloud for storage. [1]

III. METHODOLOGY

A) System Overview

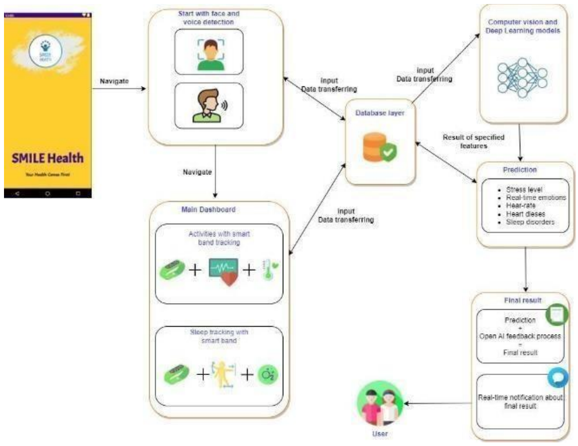

Figure 1: Overview of proposed system for machine learning and IoT based Stress Management

The smart approach proposed aims to provide stress level detection and identification of mental illnesses that may impact the human mind and physical body for all kinds of users, including children, teenagers, and adults. As depicted in Fig. 1, faces and voices can be captured by the mobile applications utilized by registered users of the system. The data concerning the face and voice are sent to the Firebase real-time database, and the stored data is forwarded to the face and voice detection model via the API path. The designed CNN algorithms process these models for the detection of stress levels and emotions in the face and voice. The results obtained from the CNN model are further processed by the Open AI system, and direct information feedback regarding the predicted result is delivered to the user.

The ability to monitor heart rate (HR) with the smart band is another important feature. Details about the user's cardiovascular health, activity intensity, and stress levels can be revealed by measuring and analyzing their heart rate using the device. This information can be particularly helpful for

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those who wish to track their exercise objectives or monitor their heart health. The smart band includes a pulse Oximeter for measuring the blood oxygen rate. Stress levels can be diagnosed by utilizing the oxygen rate and snoring level. As a result, human sleeping hours can be lower than normal. Sleep, which is the most important part of human life, can be disrupted by a lack of sleep, leading to stress. The decision was made by the research team to use a mobile phone for measuring the sound intensity of snoring and sleeping patterns.

B) Identification of mental situations, heart diseases, and sleeping disorders through inputs from the face, voice, heart rate, body temperature, blood oxygen rate, body movement rate, and snoring

1) Data collection and processing

Images of recently gathered South Asian faces were used to build Deep Learning (DL) models for the face emotion and stress level counting and prediction system. Five main classes have been identified and divided based on the identified requirements for facial emotion identification. The classes have been defined considering facial expressions and landmarks, including happy, sad, angry, natural, and stressed. These photographs were taken in varied natural situations in order to eliminate similarity between image samples. The categorization process was conducted with the assistance of psychiatric professors. Then training (80%–90%) and validation (10%–20%) sets of the photos were created. The model was then put to the test using a fresh batch of photos. Table I provides a summary of the data gathering procedure.

Table I: Data collection process for face detection model

Class Category	Training	Validation	Testing
angry	4000	200	200
happy	4000	200	200
sad	4000	200	200
natural	4000	200	200
stressed	4000	200	200

Preprocessing methods were applied to the dataset to training; a fresh batch of photos was gathered to test the model. Table II provides a summary of the data-gathering procedure.

Table II: Data Collection for Voice Detection Process

Class category	Training	Validation	Testing	Original file type	Converted file type
happy	300	50	50	mp3	jpg
sad	300	50	50	mp3	jpg
angry	300	50	50	mp3	jpg
normal	300	50	50	mp3	jpg

2) Training the detection models

For training reasons, a CNN-based model was developed to facilitate the recognition of face tension and emotion. The models for voice-based emotion and stress prediction were trained using a CNN that is based on transfer learning. Two models were trained to serve the purpose of voice-based stress level identification and voice-based emotion identification. For training reasons, a CNN-based model was developed to facilitate the recognition of facial tension and emotion. The models for voice-based emotion and stress prediction were trained using a CNN that is based on transfer learning. Convolutional (CONV) layer, rectified linear unit simplify it and enhance its accuracy. Since the generated photos had varying sizes and colors, formats were standardized to the same size (48x48), and the color mode was converted from BGR to RGB. To standardize the data, the pixel values were multiplied by 255 and then converted to numeric values between 0 and 1. To enhance the dataset size and avoid over fitting the models, data augmentation techniques such rotation, filling, horizontal and vertical shear, horizontal and vertical flipping, and zooming were used. Deep learning models were developed utilizing speech datasets in the part on identifying the mental status and stress level from the voice. The categorization process was completed based on the decimal value level of the sound wave. For voice-based emotion prediction, 5 classes were defined, while for stress level identification, 4 main classes were defined: normal, low-stressed, medium-stressed, and high-stressed. In both voice-based models, all the voice files (mp3) were converted into Mel-spectrogram images in .jpg format. Beyond that, these photos were split into training (80%–90%) and validation (10%–20%) groups. After the (ReLu) layer, pooling layer, and fully connected (FC) layer are some of the layers that make up a CNN. DNN, based mainly on Dense Layer, has been used as a Machine Learning model needed to diagnose Heart Diseases. The Same DNN (Deep Neural Network) model was used to train the body movement detection and the Blood Oxygen rate detection. A deep neural network (DNN), or deep net for short, is a neural network that has some degree of complexity, often at least two layers. Deep neural networks use advanced mathematical modeling to interpret input in complex ways.

The CNN (Convolutional Neural Network) model used to train the snoring detection Audio waves are captured through a microphone, and the sound waves will be sent through the ML model. Using Mel spectrograms, audio files are converted to image files. According to the images, the decibel range can be identified, and based on the decibel value, stress levels can be predicted.

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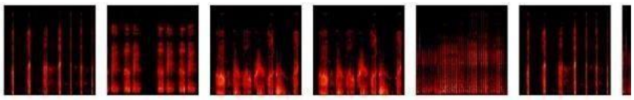

Figure 2: The view of audio graphs converted to image files

a) In this context, the involvement of a psychiatrist was crucial in identifying activities that can effectively manage stress. Various stress management techniques were likely evaluated by the psychiatrist, and specific activities that have been found to be beneficial for stress reduction were recommended. These activities could include practices such as yoga, meditation, deep breathing exercises, mindfulness techniques, or engaging in hobbies and relaxation activities.

Once the activities were identified, the next step involved finding suitable music and videos that complemented those activities. The role played by music and videos in enhancing the relaxation experience and creating a soothing environment during stress management practices was recognized. The selection of appropriate music and videos was based on their calming and therapeutic qualities, aiming to promote relaxation and reduce anxiety. To monitor the effectiveness of these stress management activities, the MAX30100 sensor was utilized by the team. The MAX30100 sensor is capable of measuring heart rate, enabling real-time monitoring of physiological changes during activities. By wearing the sensor, individuals could track their heart rate while engaging in stress-reducing practices such as yoga or meditation.

Figure 3: Connection of MAX30100 and MPU-6050 sensor with smart band

The Heart Rate (HR) was obtained using the MAX30100 sensor and Arduino board. Connections between the Arduino board and the MAX30100 sensor were established using jumper wires. The VCC pin of the MAX30100 sensor was connected to the 3.3 volts of the Arduino board, considering the appropriate voltage specified in the sensor's specifications. The SDA pin of the MAX30100 sensor was connected to the A4 pin (SDA) on the Arduino board. The development platform used was the Arduino IDE. Bluetooth communication was utilized by the MAX30100 sensor to read data from the sensor and transmit it to the phone, employing the HC-05 Bluetooth module. As depicted in Figure 14, the MPU-6050 sensor was employed to measure body temperature, which is also a factor contributing to stress. The SCL pin of the MPU-6050 sensor was connected to the A5 pin (SCL) of the Arduino board.

The heart rate (HR) values obtained from the sensor were then used to calculate an average value, offering an indication of the individual's physiological response during the activities. Furthermore, an average value calculation utilizing the heart rate data was performed to evaluate potential heart diseases. Additionally, a machine learning model was employed to analyze the collected heart rate data and identify potential heart diseases. Patterns and anomalies in the heart rate data were likely leveraged by the model to make predictions or assessments regarding the presence or likelihood of heart-related conditions. It is important to note that while indications or predictions related to heart diseases can be provided by the machine learning (ML) model based on the heart rate data, the precise determination of a heart attack occurrence may not be achievable. However, by monitoring heart rate and employing machine learning algorithms, insights into overall cardiac health can be provided by the system, and any irregularities or signs of tension or stress can be detected.

main parameter	sub parameter
Age	18-20 20-30 30+
gender	Male Female
body temperature	35°C or - 36.5°C - 37.5°C 38°C or +
stress value	no yes
disease value	no yes

Figure 4: Summary of Dataset In Heart Rate And Body Temperature

With the above data, it is possible to obtain information about heart diseases, body temperature, and the presence or absence of stress. Although the heart rate value is not explicitly mentioned here, this data is derived from the heart rate value.

b) The complex interaction between stress and blood oxygen levels highlights the physiological reaction of the body to mental and physical stress. When stress levels increase, a series of reactions are initiated by the body, including the release of stress hormones like cortisol. Consequently, the body's efficiency in utilizing oxygen decreases, and the demand for oxygen rises. Essential body processes can be deprived of energy due to stress, leading to a decrease in blood oxygen levels. Mental clarity, heart health, and overall well-

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being may be affected by long-term or chronic stress, resulting in a lack of oxygen. Monitoring blood oxygen levels can serve as a stress signal and help individuals adjust coping methods and relaxation techniques to restore equilibrium.

Leg movement detection is one of the parameters used to predict stress levels. Patients who have periodic limb movement disorder (PLMD) have fewer sleeping hours. Lack of sleep can cause mental stress. By calculating the average number of limb movements per hour, the stress level can be detected. The MAX30100 sensor was utilized by the research team to detect the blood oxygen rate, and the ADXL345 3-Axis Accelerometer was used to detect body movements. The sensor was attached to a smart band, which was worn by users during their sleeping time. A pulse Oximeter was also attached to the sensor. To connect the sensor to a microcontroller, an Arduino board was required.

c) At the severity level of snoring, low oxygen levels can be experienced by a person, which may indicate a risk of sleep apnea. The patient's sleep can be disturbed by this sleep apnea level, leading to increased stress levels. In this context, an investigation was conducted by the team to explore the dependence of stress levels on snoring level, oxygen rate, and sleeping hours. The microphone on a smartphone was chosen by the team to measure snoring levels. This approach has been deemed a creative way to determine the intensity of the user's snoring. As the user sleeps, audio data can be recorded by the smartphone, and patterns of snoring sounds can be analyzed using the microphone. Snoring events can be identified by various machine learning algorithms based on the frequency, duration, and intensity of the recorded noises. The stress level can be classified based on the decibel value of the snoring level. The lung vibrations caused by the obstruction of airflow in the upper respiratory tract are captured by the microphone. By processing this data, a snoring intensity score can be generated to assess the severity of snoring. A practical and simple method for monitoring snoring is provided by this technique.

Hours of Sleeping	Snoring Range (dB)	Blood Oxygen Range (SPO2 %)	Limb Movement Rate	Stress State
7--9	40-50	97-95	4-8	Normal
5-7	50-60	95-92	8-10	Low
2-5	60-80	92-90	10-12	Medium
0-2	80-90	90-88	12-17	High

Figure 5: Data Ranges for snoring, oxygen rate and sleeping hours

Using the above parameters, stress levels can be measured using the below data ranges.

IV. RESULT AND DISCUSSION

The models for identifying facial and speech emotions were trained using a variety of architectures (Table I), and the optimal architecture was chosen based on the loss value. After each optimization iteration, the model's performance is shown by the loss value. To assess the model's performance, images of various sizes ranging from 48 x 48 to 750 × 750 dimensions were utilized. While photos with higher dimensions (750 750) required more processing resources (a faster GPU) for model training, images with lesser dimensions (48 x 48) produced insufficient extraction of critical characteristics. As a result, 300 x 300 pixels pictures were used to train the models for best performance and accuracy.

Additionally, by modifying batch sizes (20), epochs (10–15), learning rates (0.001), steps per epoch (500–1000), validation steps (500), and verbosity (2), a decent match was attained. The adjustment procedure is essential because minor modifications can have a significant impact on the training process's calculation time, convergence speed, and processing unit usage. A dropout regularization strategy was used with various dropout rates to stop the neural network from overfitting in order to solve the problem of overfitting in CNNs during the training phase. The greatest testing accuracies were taken into consideration for choosing the optimal architectural models for the voice- and face-based models after the network settings had been adjusted. The sequential model constructed for facial emotion and stress level detection attained a calculated accuracy of 97.40%. Similarly, the voice-based stress and emotion detection models achieved a calculated accuracy of 92%. The accuracy graphs for face detection and voice detection models can be represented by the following figures, Figure 6 and Figure 7, respectively, showcasing the confusion metrics for the best models.

Figure 6: Accuracy graph of mobile net model

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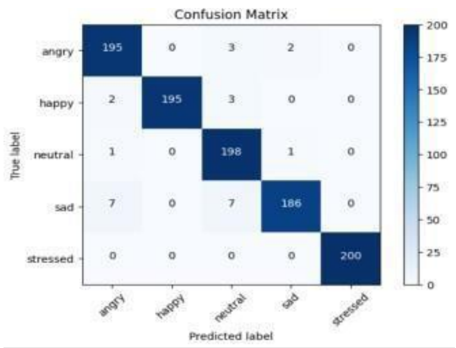

Figure 7: Accuracy graph of face detection model overview

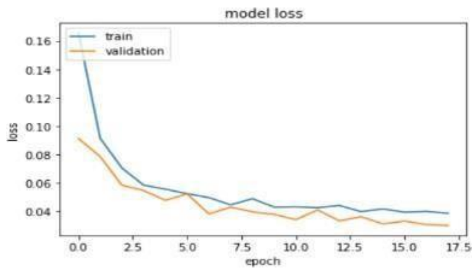

Figure 8: Line plot showing train and validation accuracy of DNN model by epochs (heart diseases)

The validation and training of the Heart disease model (Figure 8) are shown. Here the loss starts at 0.16, and by the time the 18th epoch is completed, its value has reached 0.04. The graph starts at a high value and reaches a low value. This can be concluded to be an accurate model.

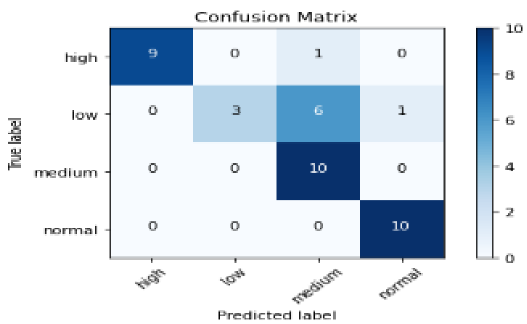

Figure 9: Confusion Matrix of the detection model evaluation

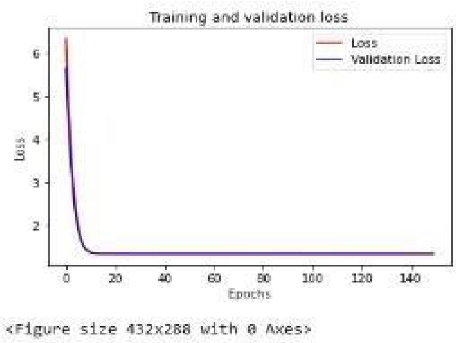

Figure 10: Line plot showing train and validation accuracy of DNN model by epochs

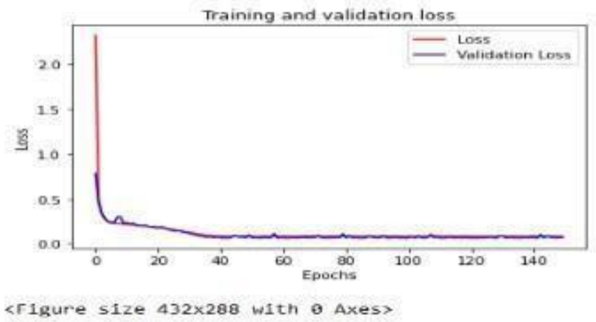

Figure 11: Line plot showing train and validation accuracy of DNN model by epochs (Body Movement)

The mobile app in this system operates differently from the other stress management systems in the industry. This system is usable by Sri Lankans who lack proficiency in English. This system can be employed by Sri Lankans with the "Sinhala" Language, enabling them to derive a superior experience from the system compared to other systems. The system operates using both the "English" and "Sinhala" languages.

V. CONCLUSION

The integration of numerous techniques, including emotion detection, voice stress detection, speech emotion detection, heart rate, snoring range, body movement level, and sleep patterns, has helped researchers advance the field of stress detection and prediction. The study team distinguished between normal, low, medium, and high stress using a number of physical and bio-physiological traits from wristband sensors, web cams, and smartphone gadgets. They were able to identify the characteristics of differentiation's most important variations as a result. The findings suggest that, employing cutting-edge machine learning algorithms and data integration methodologies, precise stress prediction is attainable. Users of this application can forecast their levels of stress, which will enhance their physical and mental health, sleep quality, and general well-being. This tool will be very helpful to Sri Lankans who need to control their stress, given that both Sinhala and English are supported. Users will be enabled by the wristband to have their emotional, physical, and mental health continuously tracked. Accurate forecasts and attractiveness will be made possible through the utilization of AI and machine learning. All the models that were developed have been proven to be highly precise and successful during training. As a result, the correction of the expected outcome is notably high.

VI. FUTURE WORKS

Numerous modifications, testing, and experiments have been left for the future because there isn't enough time. Future research may involve a deeper examination of certain

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mechanisms, the testing of novel techniques, or just plain curiosity. As a result, we can come up with numerous options for incorporating fresh concepts into the research. In our system, WIFI signals are used for connectivity, but Bluetooth technology is also an option; using Bluetooth technology requires more accurate mechanisms, trying new things out, or just plain curiosity. As a result, we can come up with numerous options for incorporating fresh concepts into the research. Additionally, English and Sinhala are now used in this system. However, we also intend to use other languages.

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