PORTABLE AI-BASED VOICE ASSISTANT FOR STRESS LEVEL MONITORING

A Project Report

Submitted to the APJ Abdul Kalam Technological University

in partial fulfillment of requirements for the award of degree

Bachelor of Technology

in

Electronics and Communication Engineering

by

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PALAKKAD 2024 - 25

CERTIFICATE

This is to certify that the report entitled **PORTABLE AI-BASED VOICE ASSISTANT FOR STRESS LEVEL MONITORING** is submitted by **LIYA DINESH K** (LNSS21EC107), **ROSHITH CV** (NSS21EC075), & **SUDHARSANA R** (NSS21EC089) to the APJ Abdul Kalam Technological University in partial fulfillment of the B.Tech. degree in Electronics & Communication Engineering is a bonafide record of the Project work carried out under our guidance and supervision. This report in any form has not been submitted to any other University or Institute for any purpose.

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DECLARATION

We hereby declare that the project report titled **PORTABLE AI- BASED VOICE ASSISTANT FOR STRESS LEVEL MONITORING** , submitted for partial fulfillment of the requirements for the award of degree of Bachelor of Technology of the APJ Abdul Kalam Technological University, Kerala is a bonafide work done by us under supervision of **Dr.LIJA ARUN,** Assistant Professor,Department of Electronics & Communication Engineering.

This submission represents our ideas in our own words and where ideas or words of others have been included, we have adequately and accurately cited and referenced the original sources.

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Abstract

A handheld AI-powered voice assistant has been created to detect and manage stress in real time. It is built on a Raspberry Pi with a camera and biometric sensors integrated in order to monitor heart rate, SpO_2 and body temperature. The system includes Raspberry Pi combined with an integrated camera along with biometric sensors.This device uses Raspberry Pi to track heart rate in addition to SpO_2 measurements and body temperature. The system uses facial expression analysis through a Convolutional Neural Network (CNN) in combination with biometric feed for improved accuracy.Based on the data gathered, the system calculates a stress score and gives personalized recommendations, such as relaxation techniques or medical recommendations. User privacy is preserved, with encrypted data storage and consent-based collection. Extensive testing in controlled and real-world settings provides reliability and continued improvement.With a voice-guided interface, the product is easy to use and accessible to all ages. Its lightweight and compact nature makes it portable, offering a convenient and proactive means of stress management at any time, anywhere.

Contents

List of Figures

Chapter 1

Introduction

Stress has become an unavoidable part of every human's life. It affects both mental health and physical health. Constant stress leads to anxiety and depression. So early diagnosis and appropriate treatment for stress are necessary. Currently, the only way to detect stress is through medical examination. Apart from traditional methods, this is an AI featuring a real-time system to measure stress through biometric sensors, face detection, and machine learning protocols. A processing unit called Raspberry Pi, a combination of inputs from several sensors, is the basic part of this model. Different types of sensors used here are a temperature sensor, an SpO_2 sensor, and a heart rate sensor, which perpetually monitor cognitive response related to stress. Aside from biometrics, Convolutional Neural Network (CNN) will analyze facial expressions. This model determines the stress features. A stress level is generated by the system by integrating all the inputs, giving an even better snapshot of the mental and physical well-being of the user. This model provides good ways to manage stress through real-time monitoring. And pushing overall wellness and psychological well-being. The model moves beyond traditional monitoring by providing immediate feedback and active engagement with the smart stress identification feature. Biometrics will continue to be used to determine a stress level by using facial features.This enables the user to react in timely manner.

The moment stress is detected, the device provides individualized interventions like breathing exercises, relaxation, or even listening to soothing music. The system is provided with a voice-guided interface, making it simple for all ages to utilize. Also, privacy and security of data is given importance to ensure that data from the users is encrypted and processed safely Portable in nature, this is a simple and handy machine learning-based stress monitoring gadget that can help one monitor his/her stress at any time and from any location. Having real-time monitoring with machine learning, this system provides an advanced way of managing stress, pushing overall wellness and mental well-being.

The smart stress detection feature enables this system to demonstrate more extensive capabilities than ordinary monitoring methods through live feedback together with proactive assistance. The continuous examination of biometric and facial expressions allows a complete assessment of stress levels which enables the user to take prompt action. These systems use artificial intelligence together with machine learning to register even minimal stress indicators which improves their accuracy. Due to its portable design and effortless operation this system makes it possible for people to manage stress properly thus leading to better physical and emotional balance in their life. By utilizing machine learning approaches the device becomes capable of differentiating between persisting and fleeting stress situations which results in enhanced long-term evaluation capabilities. Users gain access to stored stress monitoring data which provides information about what causes their stress to build to help them create appropriate preventive measures. The device functions seamlessly throughout the day because of its lightweight design and high energy efficiency without imposing any disturbances to users. The device provides quick access to stress evaluation as well as personalized relaxation techniques whenever users need them while working, at their residence or while traveling. Users benefit from the AI-enhanced stress tracking software because it offers simple operation with AI capabilities that help them personally manage their mental health while becoming proactive about stress reduction. As a system it both detects stress and implements stress reduction strategies to help users develop a healthier lifestyle in our current stressful environment.

1.1 Objective

The main goal of this project is to create a portable AI-powered voice assistant that allows real-time monitoring of stress levels using biometric sensors and facial recognition. The system is designed to offer an effective, non-invasive, and easy-to-use solution for stress detection by combining machine learning algorithms with physiological and emotional data analysis. Through the use of biometric sensors like heart rate, temperature, and SpO_2 sensors, combined with AI-driven facial expression analysis, the system constantly monitors stress levels and gives real-time feedback. This way, users are alerted and advised in a timely manner to effectively control their stress, thus enhancing their overall well-being.

Further, the project aims at increasing user accessibility in the form of a voice-controlled interface, enabling smooth interaction for users of every age group. The system is planned to provide customized stress management interventions like guided breathing exercises, relaxation, and calming music depending on the stress level detected. With a focus on portability, security, and ease of use, this AI-based solution endeavors to fill the void between standard clinical stress evaluation and real-time personal stress control, making monitoring of stress more convenient and accessible in everyday life.

Chapter 2

Literature Review

1.Advanced artificial intelligence in heart rate and blood pressure monitoring for stress management - Q Lin, T Li, PM Shakeel, RDJ Samuel

The article reports an artificial intelligence (AI) driven Fuzzy Assisted Petri Net (AI-FAS) technique to efficiently measure stress using heart rate (HR) and blood pressure (BP) monitoring. Stress is assessed using HR variability as measured through successive QRS interval in electrocardiogram waveforms. Interpretation of the ECG pattern is normally cumbersome because of the presence of noise and pathological reflexes, a problem overcome using the AI-FAS technique based on the introduction of time and frequency analysis. For blood pressure monitoring, the system records the transient time of every pulse, which indicates stress-induced blood pressure changes. Implementation of fuzzy logic into the Petri net structure maximizes the system's interpretability and precision in facilitating the treatment of complexity and variability of the physiological signals. AI-FAS met a performance level of 93.55% with precision, recall, and adaptation set at 89.01%, 89.50%, and 89.901%, respectively. The test indicated the applicability and usefulness of AI-FAS as an efficient and precise system for monitoring and evaluating stress.

2.Applications of artificial intelligence machine learning for detection of stress: a critical overview - AFA Mentis, D Lee, P Roussos

Psychological distress has a significant effect on human pathophysiology and physiology, leading to conditions like suicidal behavior, sleep disorders, metabolic syndrome, and autoimmune diseases. Hence, early identification and control of chronic stress are crucial to avoid such health conditions. The paper underlines the increasing role of Artificial Intelligence (AI) and Machine Learning (ML) in biomedicine, with a focus on diagnosing, monitoring, and predicting stress-linked conditions.It reports findings from past research that indicate AI and ML models are capable of predicting stress with high accuracy and distinguishing between normal and abnormal brain conditions, such as post-traumatic stress disorder (PTSD), with approximately 90% accuracy.The authors argue that while current AI/ML technologies do accurately quantify exposure to stress, the future studies must tackle detecting chronic distress to make it clinically more useful. The paper also introduces Swarm Intelligence (SI), an AI paradigm that uses ensemble learning techniques to solve complex problems, e.g., stress detection. SI is promising for clinical applications owing to its effectiveness and privacy-sustaining nature. The authors point out that the incorporation of AI, ML, and SI into routine clinical practice can greatly benefit patients and the medical community alike through improved stress diagnosis and management. They conclude by calling for more research to make AI-based stress detection a mainstream clinical tool.

3.AI Driven Psychological Pattern Analysis through Deep Learning-Enhanced Wearable Monitoring Systems - MA Jawad, MA Mohammed, A Al-Hilali The paper introduces a Deep Learning-aided Wearable Monitoring System (DLWMS) targeting psychological pattern analysis and mobile phone-based stress monitoring. In contrast to the common standardized stress assessment methods, DLWMS targets real-life, mobile conditions, making it possible to identify tension parameter fluctuations in daily life.The system is equipped with multisensory monitoring hardware, such as sensors and eye-tracking glasses, to capture psychophysiological measures. Through the exploitation of sophisticated quantitative monitoring methods, the system provides a more precise and dynamic measurement of stress patterns, something which can be beneficial for Information Systems (IS) studies—a discipline where traditional approaches are generally constrained by real-time stress identification.The research identifies the feasibility and acceptability of applying m-Health technologies in psychophysiological health education. The participants showed a positive reaction to the wearable stress monitoring system, suggesting its potential use in wider applications in health and safety management.The authors indicate that the technology has the potential to be most valuable in high-stress situations or vulnerable populations and assist researchers and healthcare workers in refining safety procedures and maximizing mental health interventions. The research highlights the increasing significance of AI-based m-Health technologies for monitoring stress and recommends future consideration of such systems in clinical and research environments.

4.Review of stress detection methods using wearable sensors G Taskasaplidis, DA Fotiadis, PD Bamidis This paper addresses current work in stress monitoring using wearable sensors. The review addresses the causes of stress, its impacts on health, and why stress monitoring is essential in an attempt to improve psychosomatic health. The paper recapitulates biological signals, biomarkers, body postures, speech characteristics, and trembling hands as manifestations of stress. The review also identifies various stress recognition technologies and analytics methods. It provides a long reference guide to future work in the field with opportunities and the scope of potential improvement of stress monitoring solutions.This paper presents an overall review of stress detection methods using wearable sensors, and their application to enhance mental and physical health.Additionally, it describes how body movement, posture, speech rhythm, and hand shaking can be crucial for identifying stress levels.The study refers to a wide range of wearable devices and data processing techniques used in stress detection and provides a comparative analysis of their effectiveness.

5. Towards Real-Time Facial Emotion-Based Stress Detection Using CNN and Haar Cascade in AI Systems - AB Yadav The article proposes a stress detection system using Convolutional Neural Networks (CNNs) and Haar Cascade classifiers, leveraging the best of both methods for high accuracy. Stress is detected using facial expressions, which are of significant importance when it comes to expressing emotions, particularly stress.The approach includes preprocessing input images to enhance their quality, followed by face detection through Haar Cascade classifiers, which precisely detect facial areas even under different lighting conditions and orientations. The detected faces are resized and normalized to produce uniform inputs for subsequent processing. Lastly, the CNN model classifies the images according to stress indicators, recording promising accuracy when tested on publicly available datasets.The proposed AI-based approach provides future applications in stress management, mental health assessment, and tailored therapies. Through facial expression analysis, the system offers an non-invasive and effective means to track stress levels in real-time. The use of CNN and Haar Cascade improves the precision and effectiveness of the system, which thus presents a strong tool for monitoring psychological well-being. This study draws attention to the increasing importance of AI in affect recognition and the potential contribution of AI to mental health solutions.

6. Depression detection using emotional artificial intelligence and machine learning: A closer review - ML Joshi, N Kanoongo

The research investigates the deployment of Machine Learning (ML) and Artificial Intelligence (AI) systems for depression detection purposes techniques for the detection of depression. Previous research has employed various detection methods using both facial features and affective chatbot and social media text analysis while also assessing depression. This paper implements Naive Bayes together with Support Vector Machines (SVM) as well as Long Short-Term Memory (LSTM) combined with Recurrent Neural Networks (RNN) and Artificial Neural Networks (ANN). The research details how depression detection functions via emotional recognition. The earliest signs of depressive behavior serve as recognizable elements through the analyzed data.The results show that all these limitations apply to such AI-based methodologies and their application among various age groups. The research demonstrates the necessity of automated systems that should perform early intervention while monitoring intervention in mental health.

7.Evolutionary inspired approach for mental stress detection using EEG signal - LD Sharma, VK Bohat, M Habib, AM Al-Zoubi

The work in this research offers a new method for the detection of stress through short-length EEG signals that considers the acute problem of stress, which directly impacts mental as well as physical well-being. Long-term stress may cause severe health issues, so early detection is crucial to control it efficiently. Electroencephalogram (EEG)-based methods have been widely researched for the detection of stress since stress largely impacts brain activity and structure. Nevertheless, current non-invasive techniques need predictive accuracy and reliability improvements.Non-invasive features in this study were extracted by decomposing EEG signals with the stationary wavelet transform (SWT) and by using entropy-based features that could identify key stress-related patterns. The selected features were next classified with multiple supervised machine learning models to separate stress and non-stress states. Evolutionary-inspired optimization algorithms were used to improve classification accuracy. Particularly, the whale optimization algorithm (WOA) was employed to optimize support vector machines' parameters while, at the same time, feature weighting was done.

8.State-of-the-art of stress prediction from heart rate variability using artificial intelligence - Y Haque, RS Zawad, CSA Rony, H Al Banna The article discusses advances in AI-powered prediction of stress with heart rate variability (HRV) data, which captures the time difference between two consecutive heartbeats. The widespread availability of miniature sensors and affordable wearables has made lifestyle monitoring and physiological signal detection more feasible.HRV is also widely employed as an indicator of stress, depression, and anxiety and is therefore a significant metric in the evaluation of mental health. The present paper presents a critical review of 43 studies that utilized various AI and deep learning (DL) models for predicting stress from HRV data.It offers an extensive review of sensing technologies, pre-processing, and prediction models and emphasizes the accuracy and efficiency of AI in detecting stress.HRV is commonly used as a measure of stress, depression, and anxiety and thus serves as an important metric in the assessment of mental health.The research also critically analyzes which various Machine Learning (ML) algorithms have been applied in order to improve the accuracy of stress prediction. It also determines the most important features and methods that enable enhanced model performance and gives insights on the difficulties in employing HRV for stress measurement, including data volatility and noise. The authors propose mitigation methods to overcome such constraints for improving the reliability of future AI-based stress detection systems. Overall, the paper brings out the significance of AI-accomplished methods in monitoring mental health and offers valuable suggestions for developing more efficient and accurate models for predicting stress.

9. Psychological Stress Detection Through Speech Using Machine Learning - N Kulasooriya, S Menaka, I Prabuddhini, C Karunatilake This paper investigates the identification of psychological stress from Sinhala speech signals based on machine learning. A special dataset of 144 speech files was prepared for training and testing. The Fast Fourier Transform (FFT) converted speech signals into frequency data while the system utilized Mel Frequency Cepstral Coefficients (MFCC) characteristics as its main features. The research employed Support Vector Machine (SVM) and Artificial Neural Networks (ANN) for detecting and classifying stress in subjects. The experimental data indicated that Support Vector Machine produced 59% success while Artificial Neural Networks achieved a slightly higher accuracy rate of 63%.

10.Artificial intelligence (AI)-enabled technology in medicine-advancing holistic healthcare monitoring and control systems - KC Rath, A Khang, SK Rath, N Satapathy This chapter examines the capability of AI-powered integrated medicine in reshaping holistic health monitoring and cancer therapy. The strategy integrates several modalities of treatment, viz., radiotherapy, chemotherapy, immunotherapy, targeted therapy, hormone therapy, precision medicine, and new approaches such as CAR-T cell therapy, cryotherapy, and phototherapy. The system uses AI algorithms to analyze large patient information, i.e., medical histories, genetic makeups, and lifestyle information, to design personalized treatments. Such an evidence-based data-driven approach further strengthens decision-making by healthcare providers for more specific and adaptive interventions.Real-time monitoring and control systems improve patient safety also by enabling on-time intervention and adjustment of care. The complement of complementary treatments and palliative care ensures comprehensive attention to health. The data aggregation for patient information also promotes advances in cancer research and studies of population health, which create better understanding and care methods. The authors observe that the integrated medicine with AI has great potential to enhance the outcomes of cancer therapy, improve the quality of life in patients, and drive innovation in cutting-edge cancer care.

11. Frontal lobe real-time EEG analysis using machine learning techniques for mental stress detection - O AlShorman, M Masadeh, MBB Heyat, F Akhtar, H Almahasneh, GM Ashraf, A Alexiou

This essay investigates the way AI Chat GPT can maximize the well-being of students in intelligent higher education learning spaces. The research is based on extensive literature review through examination of published works, empirical data, and research studies concerning higher education on the ways in which AI Chat GPT can be applied.findings present potential benefits, such as personal assistance, mental health assistance, and academic guidance, as well as challenges of ethical concerns and AI dependence. The study emphasizes that AI should be used ethically in order to obtain the optimum beneficial impacts on the students. However, empirical findings and research studies are necessary in order to learn more about its long-term implications on students' well-being.

12.AI-Enabled Smart Wristband Providing Real-Time Vital Signs and Stress Monitoring - N Mitro, K Argyri, L Pavlopoulos, D Kosyvas

This paper introduces a low-cost, machine-learning-capable wrist-worn device for real-time stress monitoring during mass passenger ship evacuations. The wearable tracks passengers' physiological condition based on a PPG signal to obtain biometric information like pulse rate and oxygen saturation level. It has an in-built machine learning pipeline based on ultra-short-term pulse rate variability for stress identification. This paper proposes a low-budget, machine learning-based wrist-worn device that can detect stress in real time for large passenger ship evacuations. The wearable tracks passengers' physiological condition via a PPG signal to collect biometric information like pulse rate and oxygen saturation level. The wearable has an ultra-short-term pulse rate variability-based machine learning pipeline embedded for detecting stress.

Chapter 3

System Development

3.1 Core Components

1.Raspberry Pi 4 Model B

The main computer of the project uses Raspberry Pi 4 Model B as its central processor.Raspberry Pi operates as an intermediary that links microphones sensors and speakers.The system allows voice commands to seamlessly communicate with real-time data with the help of speakers.The speech recognition functionality executed by Raspberry Pi depends on AI-driven analysis. The system benefits from these models to effectively recognize and answer user questions.This system also acquires data from stress-monitoring sensors through its built-in measurement capabilities.The system employs heart rate or skin conductance sensors to measure stress levels that it analyzes through its software program. The wireless capabilities of Raspberry Pi enable it to join AI models on the cloud.Raspberry Pi achieves better precision together with enhanced storage capabilities through cloud connectivity.

Figure 3.1: Raspberry Pi 4 Model B

2.MAX30102 sensor

The MAX30102 sensor delivers real-time measurements of heart rate combined with oxygen saturation SpO2 levels because these physiological markers represent the primary indicators of stress. Data acquisition and processing task between MAX30102 sensor and Raspberry Pi occur through the I2C protocol connection. Stress levels of users are calculated by measuring variations in heart rate and SpO2 from the system which provides appropriate feedback using an AI-based voice assistant. The MAX30102 device offers excellent utility in portable stress monitors because its small size combined with low power consumption suits applications in wearable devices for stress measurement. The implementation of AI processing enables the assistant to deliver personalized recommendations and relaxation exercises and reminder functions thus improving the mental wellness monitoring system significantly.

Figure 3.2: Max30102

3.Photoplethysmography (PPG) sensor

The PPG sensor delivers optimal functionality for detecting heart rate and blood perfusion outside the body which serves as a key component in stress monitoring systems.The device functions by showing light on skin tissue while detecting variations in the amount of absorbed light which results from blood flow modifications. The system reveals extensive details about heart rate and HRV measurements along with stress injury signals.

The PPG sensor is combined with Raspberry Pi to monitor physiological signals in real-time. Based on the variations in heart rate and HRV, the AI-powered voice assistant can identify the level of stress of the user and provide customized feedback or relaxation recommendations. This real-time monitoring helps the system become more proactive in stress management. The small, wearable-friendly PPG sensor structure allows the device to be maintained as portable and comfortable to use, thus extremely effective for repeated stress measurement.

Figure 3.3: Photoplethysmography (PPG) sensor

4.DHT11–Temperature and Humidity Sensor

DHT11 sensor is a ubiquitous digital temperature and humidity sensor for environmental conditions such as temperature and humidity. Individual stress levels may be influenced by such environmental conditions of temperature and humidity, and integrating the DHT11 sensor with Raspberry Pi enables the voice assistant powered by AI to monitor such external factors.DHT11 sensor reads temperature and humidity real-time, and they are analyzed along with physiological metrics like heart rate and level of SpO. Unwanted humidity and temperature could induce discomfort and stress.

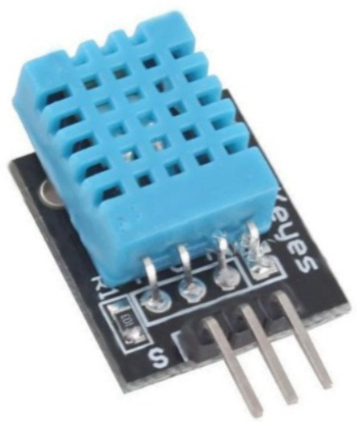

Figure 3.4: DHT11–Temperature and Humidity Sensor

3.2 System Architecture

The block diagram illustrates a real-time stress monitoring system using facial recognition, biometric sensors, and Raspberry Pi to quantify the stress levels and recommend customized cures. The system collects physiological data from a temperature sensor, heart rate sensor, and SPO sensor, which help identify stress markers from body variations. The system also monitors facial expressions for signs of stress using a Convolutional Neural Network (CNN)-based face recognition system. These inputs are input to a Raspberry Pi, which generates a stress score using machine learning algorithms. Based on the level of stress, the product offers personalized cures, i.e., guided breathing exercises, listening to soothing music, or offering professional advice. The voice interaction makes it accessible to all, and hence a small, portable, and useful tool to control stress. The system also integrates real-time feedback, allowing continuous monitoring and adjustments based on the user's stress levels. The machine learning model adapts over time, improving its accuracy in recognizing stress patterns and recommending effective solutions. Additionally, the system can store historical stress data, enabling trend analysis and long-term health insights. Its compact design and low power consumption make it ideal for personal and professional use, offering a user-friendly interface through both visual and voice guidance.

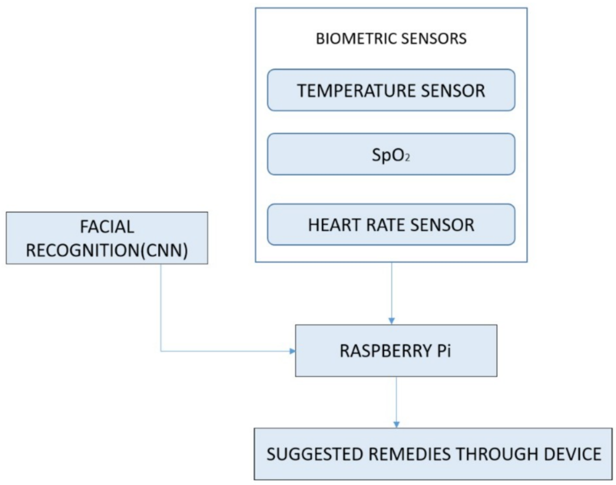

Figure 3.5: Block diagram of Portable AI-Based Voice Assistant For Stress Level Monitoring

3.3 Methodology

The software part includes Image Pre-processing, Convolutional Neural Network Training and Face detection and Image Acquisition

A. **Image Pre-processing**

Convolutional Neural Network (CNN) model development in deep learning for image classification is researched in this work. The initial step is pre processing of images when techniques such as scaling, normalization, and data augmentation are utilized to make the model more accurate and general. The Adam optimizer is applied subsequently to train the model following a well-formatted CNN, designed to capture key spatial features. There are multiple methods used to measure its performance, and visualizations are created in order to track trends in accuracy and loss, which provide insight into how well the model learns and improves with time.

1. **Data Collection and Loading**

The information were organized into a number of files, each one of them a different emotion, say ”happy” or ”angry.” This friendly organization facilitated the process of associating images with their corresponding labels during data loading.

2. **Loading and Colour Formatting**

The pictures were imported with the OpenCV library (cv2.imread) and were all converted to RGB mode to be colour scheme homogeneous in the entire dataset. This facilitated seamless compatibility with various machine learning platforms. Every class also received a unique numerical label for the model to process smoothly.

3. **Uniform Image Dimensions** The original dimensions of the images were different, so all of them were resized to 50×50 pixels to ensure consistency in input sizes. Two advantages of standardizing image sizes were reducing computational complexity and ensuring the compatibility of the dataset with the CNN model, which accepts fixed input sizes.

4. **Pixel Value Scaling** Pixel values, originally in the range 0 to 255, were normalized to be in the range [0, 1] by dividing all the values by 255. This was performed to ensure numerical stability during training because it prevented huge gradients and made optimization overall more efficient

5. **Splitting Data** The information was divided into two main sets: the training set,

which constituted 80% of the data, and the testing set, which comprised the remaining 20%. The training set was used to enable the CNN to learn and pick up distinctive features that were unique to each class such that the model would be highly trained using diversified data. Simultaneously, the test subset was employed to examine the model's performance on unseen images and obtain an insight into its power of generalization. Equipped class distribution within both subsets was maintained by carrying out stratified sampling, under which the ratio of each category was fixed across the dataset.

6. **Augmentation for Diversity** To diversify the training set and enable the model to generalize better, a few data augmentation techniques were utilized. Flipping was utilized to create alternative views so that the model could identify objects from various orientations. Small-angle rotations were implemented to simulate minimal positional changes, making the model robust to orientation variations. Scaling was also applied to vary image sizes, simulating varying distances of viewing. These improvements not only diversified the dataset but also enhanced the model's capacity to learn and perform well when it is faced with new, unseen images.

B. **Convolutional Neural Network Training**

Three convolutional layers with ReLU (Rectified Linear Unit) activation were used to identify essential patterns in the input images, such as edges, textures, and shapes. These patterns formed the basis for higher-level feature extraction.

Hardware part includes collection of data from biometric sensors and integration of data from facial recognition.

1.**Model Compilation and Training**

After each of the convolutional layers, max-pooling was employed in order to down sample the feature maps, i.e., reduce them in size with a loss in spatial details that was not actually substantial. Down sampling proved useful in cutting down the computational expenses simultaneously while retaining significant features that assisted in correct identification. Max-pooling also aided in the creation of translational invariance to make sure that even if objects on images occupied slightly different positions, the model would work. To reduce the risk of overfitting, a dropout layer with 25% was added. The methodology of this method included deactivating randomly part of the neurons during training in a way that the model had to learn more diverse features rather than heavily depending on specific patterns. Therefore, the model learned a higher ability to generalize to new data. Fully connected layers with the application of ReLU (Rectified Linear Unit) activation were used after feature extraction. These layers transformed the extracted features to a more ordered and more understandable representation so the model can become better able to distinguish among multiple categories. Finally, the network concluded with an output layer employed with a softmax activation function. The final one converted the transformed data to probabilities scores to enable the model to classify the image into one among the five specified emotion categories.

2.**Loss Function and Optimization Strategy**

The model employed the sparse categorical cross-entropy loss function to quantify the disparity between the predicted and actual labels, thus being perfectly suited for multi-class classification tasks. The loss function assisted the model to learn the differences between categories well by inflicting penalties on incorrect predictions.For the realization of effective and stable learning, the Adam optimizer was used. The optimization method was responsible for dynamically scaling down the learning rate during training. Through adjusting the learning rate from the gradients, Adam enabled the model to converge better, thus enhancing its potential to achieve maximum performance without falling into problems of slow learning or being trapped in suboptimal solutions.

3. **Training Configuration**

The training procedure was formulated to strike a balance between performance and efficiency. It was performed in mini-batches of 32 images, which offered a good compromise between the use of computational resources and model stability during updates. The model was trained for 5 complete epochs, with sufficient iterations for the network to learn patterns and features within the dataset effectively. In order to enable the model's generalizability to unseen data, 20% of training data was reserved as a validation set.

4. **Model Evaluation and Performance Analysis**

To assess the performance of the model after training, a number of metrics were utilized to provide an all-around measurement. Accuracy counted the percentage of images correctly identified, giving an overall measure of the success of the model. A confusion matrix was used to examine the pattern of correct and incorrect predictions by all classes to provide insights into particular strengths and weaknesses. Further, sensitivity and specificity were computed in order to gauge the model's performance in distinguishing true positives and true negatives, respectively. A classification report in detail was also generated, noting precision, recall, and F1-scores for all emotion categories, which can be used to better understand the performance of the model. In order to save and utilize the model, it was stored in different formats such as JSON (JavaScript Object Notation) HDF5 (Hierarchical Data Format 5) and the complete model structure to allow for flexibility and compatibility across platforms. The trained model was applied to unseen data to assess real-world usability. For further study of the training process, graphs of performance were created to present trends in loss and accuracy over epochs. These plots provided valuable insights into the learning pattern of the model, where it was doing well and where it needed improvement.

5.**Face Detection and Image Acquisition** The process is initiated using OpenCV and a webcam-based real-time face detection. For human face detection from the frame of the video, the system utilizes the Haar Cascade classifier (Pre-trained model) . A fixed number of frames are captured by the system (50 frames in our case) for the purpose of acquiring multiple samples for stress estimation. Frames are flipped horizontally for consistency and converted to grayscale mode for quality enhancement of detection of face features. The faces detected are highlighted in boxes such that extraction of meaningful facial features for further use is easier.

6. **Facial Feature Extraction and Image Processing** When a face is detected, the facial features of the face region of interest (ROI) is cropped from the grayscale image. The extracted face is resized to a standard size of 50×50 pixels so that there is standard input to the deep learning model. The CNN model will only accept RGB images, and therefore the extracted grayscale face is transformed back to three-channel RGB. The processed images are then stored in a structured NumPy array with batch dimensions and can now be fed as an input to the CNN-based stress detection model. This is done to standardize facial data so that accurate predictions can be made.

7. **CNN Model Prediction** An existing pre-trained Convolutional Neural Network (CNN) model trained on facial stress datasets is imported to analyze the recorded frames. Stored facial photographs are fed to the CNN, which analyzes them to estimate

stress levels based on learned patterns of facial expressions by the CNN. The model returns stress scores for each frame indicating the likelihood of stress observed on the subject's face. These measurements are averaged across all frames recorded to obtain a more stable and uniform stress measurement, which reduces errors from facial expressions in instances.

8. **Stress Level Calculation and Data Storage** To find the ultimate stress level, the system calculates the average of all the predicted stress scores over the captured frames. This averaging method smoothes out fluctuations and gives a more stable stress measurement. The calculated stress level is then shown on the screen and saved in a text file. This accumulated data may be used for additional analysis, long-term monitoring of stress patterns, or even with external health monitoring systems. The process may be improved by adding more physiological sensors or improving the CNN model with larger, more diverse datasets.

Hardware part includes collection of data from biometric sensors and integration of data from facial recognition.

Physical data in real time is being read directly from an individual's body. This is done with the assistance of biometric sensors such as temperature sensor, SpO2 sensor and heart rate sensor. The ambient body temperature is measured by temperature sensor DHT11 (Digital Humidity and Temperature sensor) [6]. Body temperature is different for every individual, normal body temperature is 37°C. Stress may raise temperature above 37°C or decrease below or constant. A severely stressed individual temperature can rise beyond 41°C as well. So it simply relies on the stress level. SpO2 sensor (MAX30100) monitors the percentage of oxygen in the blood. A normal human is maintaining Oxygen Saturation level between 95% to 100%.The SpO2 level of a stressed individual may fall below 90%. It is capable of producing a severe health problem. Heart rate sensor (PPG sensor) detects the heart beat rate. 60 to 100 beats per minute is the healthy individual's normal heart beat rate while that of a stressed individual is up to 120 beats per minute.

The computed stress value is compared with pre-defined threshold ranges and then the system categorizes the stress level into one of three levels: low, moderate, or high. Low stress will generally imply an acceptable state which might not call for direct action but would welcome preventive treatment such as relaxation exercises or mindfulness.

Moderate stress will imply a stronger effect on the well-being of the person and will require interventions like relaxing music, deep breathing exercises, or brief pauses in order to curb stress levels. Excessive stress, which is a potential threat to physical and mental well-being, can induce more intense interventions, like booking doctor's appointment. So the real-time stress monitoring system detects stress and provides relaxation techniques to overcome stress.

Chapter 4

Result and Discussion

The proposed model after training and validation with CNN, a graph of model accuracy with epochs is obtained. Training accuracy starts at around 50%, implying that the model has little predictive power at the beginning. As training progresses, accuracy gradually increases to approximately 75% at epoch 4. This positive trend signifies that the model becomes increasingly adept at identifying patterns and categorizing data correctly, demonstrating appropriate learning and enhanced generalization for each epoch.

1.Training and Validation Accuracy

i.X-Axis (Epochs): Shows the number of passes that the model undergoes in order to traverse the entire training data set. The line begins at 0 and goes up until 4, which shows that the model has been trained on 5epochs.

ii.Y-Axis (Accuracy): Represents the proportion of samples that are predicted correctly by the model. Starts from 0.5(50%) and goes up to 0.8(80%). The higher the accuracy the better the model

At epoch 0: The training accuracy begins at about 50% which means the model has little or no capacity for correct prediction at the initial stages since it has not learned the patterns of the training data yet.

Epochs 1 to 4: The blue line indicates a trend upwards, approaching approximately 75% when is epoch 4 showing the model learning and enhancing its capacity to classify the training data.

2.Training and Validation Loss

The Training and Validation Loss graph indicates a linear reduction in the training loss as well as validation loss with respect to the epochs. It illustrates that the model is minimizing its errors and getting better at predicting. Validation loss ¡ training loss indicates that the model is generalizing nicely and is not overfitting. In general, the plots are indicating that the model is learning stress level trends nicely, so the model will be stable to implement in real-time monitoring systems.

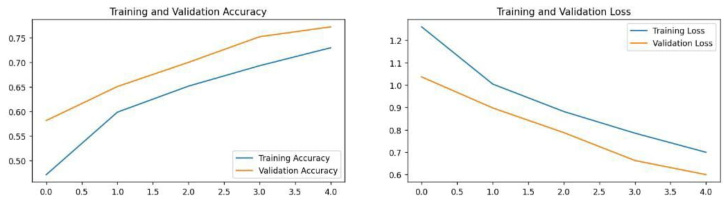

Figure 4.1: (a) Epoch Vs Accuracy (b) Epoch Vs Loss

Validation Accuracy (Orange Line) Epoch 0: The validation accuracy starts off slightly better than the training accuracy, perhaps because of randomness at initialization or lucky patterns in the validation set.
Over epochs: The validation accuracy also rises steadily but remains a little behind the training accuracy in the later epochs. For epoch 4, the validation accuracy also holds at 72-73%, indicating how well the model can generalize to new data.
Both the training accuracy and validation accuracy improve with the number of epochs, which shows the model is correctly learning the patterns of the data. This also reflects that the training is going in the right direction without any sharp divergence or saturation in the performance. There is a relatively very small difference between the training accuracy and validation accuracy (3-5% at epoch 4). It means good generalization because the performance of the model on training and validation sets is similar. If training accuracy rose significantly and validation accuracy saturated or dropped, then it would be an indication of over fitting. But the graph reflects balanced performance.
Facial Recognition and Stress calculation:
A webcam captures photos, and photographs are processed to rectify format and are employed for facial identification and stress analysis. The measurement of the level of stress is performed based on a formula using various facial features: Stress level = 0.2 $\times$ Mouth Curvature - (0.3 $\times$ Brow Furrow Intensity) + (0.5 $\times$ Eye Openness Score).

The Average Stress Level is determined by summing up all of the stress predictions and dividing the sum by the number of predictions. Three levels of stress are differentiated based on this average value: Low Stress: 0 to 0.3,Moderate Stress: 0.4 to 0.6, High Stress: 0.7 to 1.

2. **Confusion Matrix**

The provided confusion matrix is a five-class classification problem, with each row being the actual class (true label) and each column being the predicted class (model output). The diagonal values are correct classifications, and off-diagonal values are misclassifications. The model is very good at classifying class 1, with 4,002 correctly classified instances, and other classes have different degrees of misclassification. For example, class 0 is mistakenly identified with classes 2 and 3, as represented by 250 and 243 misclassified samples, respectively.

In the same vein, class 3 is confused with class 2 in 444 instances, implying the model cannot distinguish between these two classes. Class 4 performs least poorly with 1,654 accurate predictions and few false positives. These errors pinpoint areas of improvement, including improvements in feature selection, balancing data, or optimizing hyperparameters to make the classes more separable. In general, despite the model performing well on overall classification, even for class 1 its patterns of misclassifications indicate possible areas for improving optimization for better accuracy over all classes.

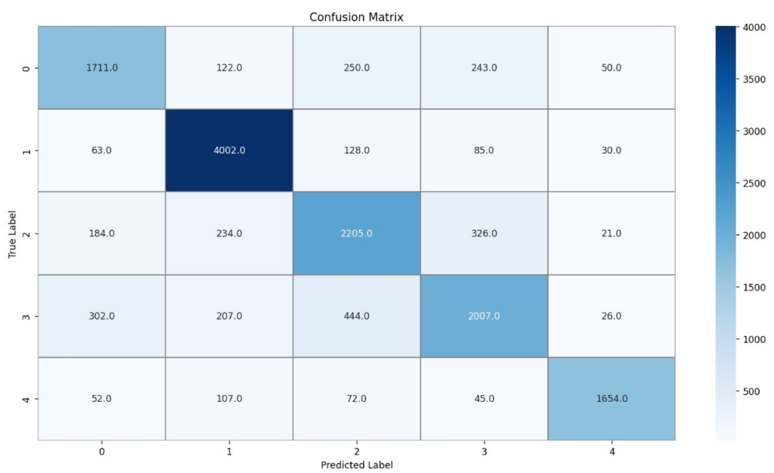

Figure 4.2: Confusion Matrix

LOW STRESS

When there are neutral or happy facial expressions provided as an input, there are few examples of stress-characteristic features such as furrowed brows or mouth curvature reflecting tension. Since these expressions tend to be those of relaxation or positive emotional events, the measure of stress that is taken is low. The algorithm used for stress prediction assigns lower scores to features observed in experiences that are calm, and that is why there is an output that is far within the low-stress category. The individuals exhibiting neutral or smiling faces belong to the low-stress category, thus affirming the reliability of stress measurement using face recognition.

```
>>> %Run ff.py
 2025-01-27 12:56:51.760389: I tensorflow/core/platform/cpu_feature_guard.cc:193] This TensorFlow binary is optimized with oneAPI Deep Neural Ne
 twork Library (oneDNN) to use the following CPU instructions in performance-critical operations:  AVX AVX2
 To enable them in other operations, rebuild TensorFlow with the appropriate compiler flags.
 2/2 [==============================] - 0s 7ms/step
 Average Stress Level: 0.07069949
>>>
```

Figure 4.3: Average Value of Low Stress

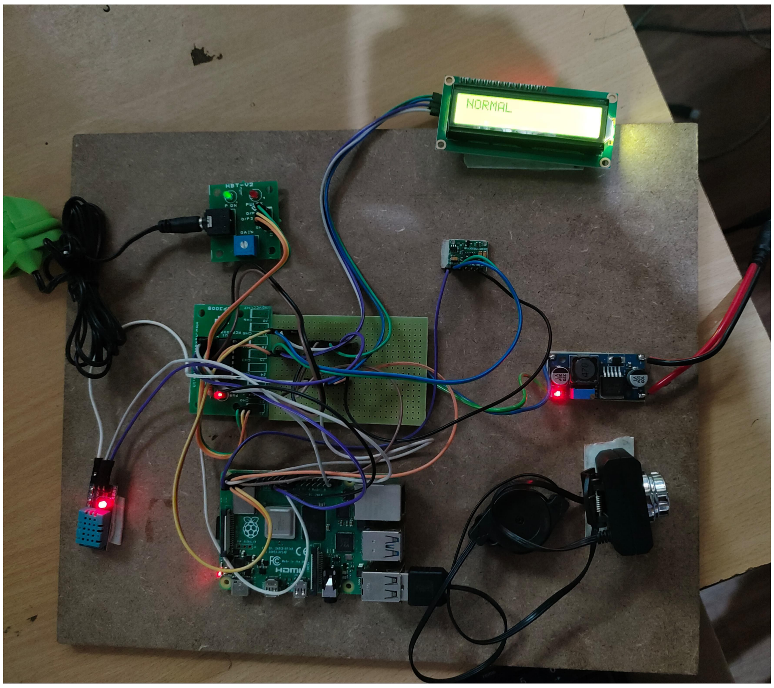

Figure 4.4: Low Stress

MODERATE STRESS

When images of surprised faces are used as input, the system identifies moderate levels of stress based on some facial features related to surprise. A surprised face usually involves widened eyes and eyebrows that are raised, which are contributing factors to eye openness and furrow brow intensity. Although mouth curvature could mitigate some of the stress indicators, the net effect is to yield a moderate level of stress output. Based on the stress calculation formula, the facial features here do not represent excessive relaxation or excessive tension, and therefore put the level of stress in the moderate category. Consequently, surprise faces are usually categorized as moderate stress.

If moderate stress is detected breathing excercise is the remedy suggested. The voice assistant helps by counting ”breathe in” and ” breathe out” for 5 times.

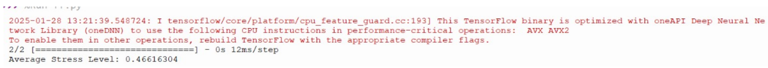

Figure 4.5: Average Value of Moderate Stress

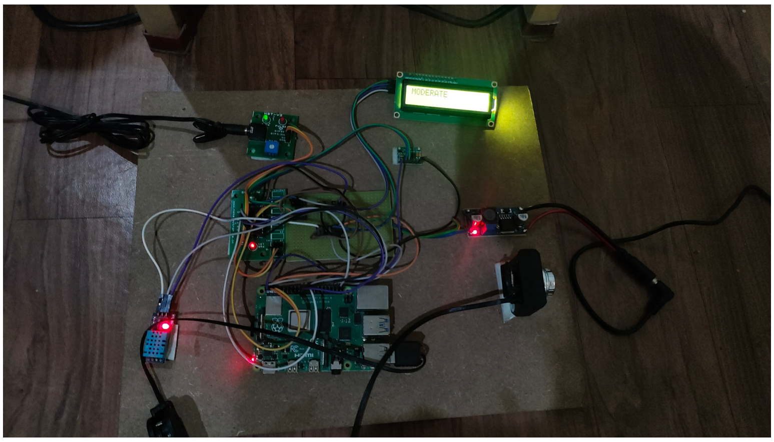

Figure 4.6: Moderate Stress

HIGH STRESS

Upon entering angry facial expressions, the system determines a high amount of stress from the clear facial features of anger. An angry face typically has intense brow furrowing, screwed-up eyes, and tensed lips, all of which play significant roles in the stress calculation formula. More intense brow furrowing and more closed eyes increase the overall stress score, catapulting it into the high-stress zone. Since anger is closely connected with heightened emotional tension and arousal, the system accurately labels such displays as high stress, reflecting the person’s high level of emotionality.In case of high stress , temprorary relaxation technique is used that is playing a song in youtube and listening to it can reduce stress for some extend.Sometimes it will be highly essential to consult a doctor so an automatic hospital appointment booking is being done.

```
>> %Run ff.py
2025-01-27 12:50:43.191965: I tensorflow/core/platform/cpu_feature_guard.cc:193] This TensorFlow binary is optimized with oneAPI Deep Neural Ne
twork Library (oneDNN) to use the following CPU instructions in performance-critical operations:  AVX AVX2
To enable them in other operations, rebuild TensorFlow with the appropriate compiler flags.
2/2 [==============================] - 0s 0s/step
Average Stress Level: 0.9200077
>>
```

Figure 4.7: Average Value of High Stress

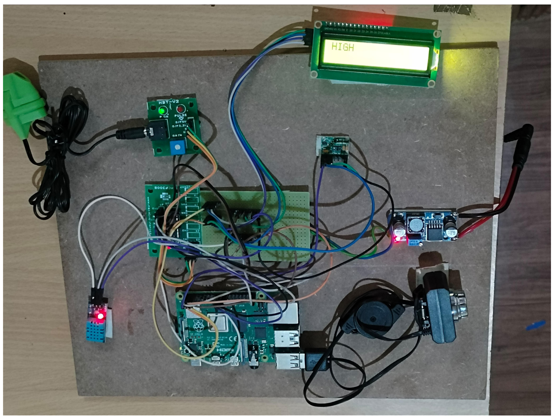

Figure 4.8: High Stress

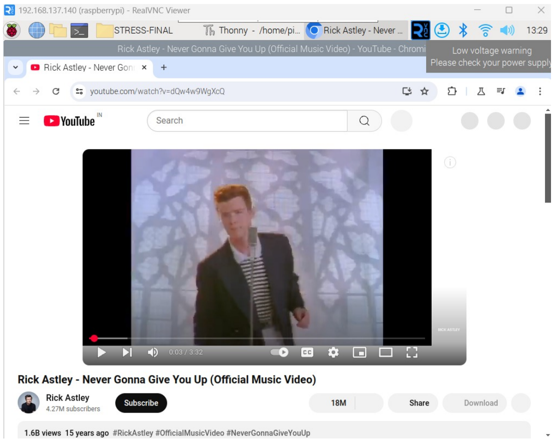

Figure 4.9: Youtube song being played

Hospital Appointment Booking

Patient Details

Name	sudharasana
Age	22
Appointment Status	APPOINMENT_BOOKED
Timestamp	07/03/2025, 13:41:15

Figure 4.10: Hospital Appoinment Booking Slip

Chapter 5

Conclusion

The development of Portable AI-Based Voice Assistant is tailored to deliver real-time stress monitoring and assessment via a blend of facial recognition and biometric sensors. The system employs Convolutional Neural Facial expression analysis networks (CNNs) which enable it to analyze stress levels with high precision. Furthermore, biometric monitors such as heart rate, SpO2 (oxygen saturation), and temperature sensors, and these are integrated to gather physiological indicators of stress. With all these multiple data sources integrated, the system builds a compare-multimodal and holistic stress detection system whose accuracy is enhanced to its predictions. To provide correct evaluations, the method entails data augmentation,image preprocessing, and training the CNN, which refine the model's performance

The virtual assistant is always looking for information coming in real-time, and detection of subtle facial expression, heart rate, and body temperature to more precisely calculate stress levels. Once stress is detected, the system computes a stress score and classifies it into one of the three levels of low, moderate, or high, assigning the systematic evaluation of the user's current physiological and emotional state. These categorizations enable the AI assistant to provide adaptive and personalized interventions based on the level of low-stress users. For low-stress users, the assistant will suggest simple mindfulness-based interventions or brief relaxation procedures. For an intermediate strength of stress,it may also mean guided meditation, calming music, or deep breathing. In cases of high stress, the system can offer more intense interventions, like suggesting that the user seek professional counseling, exercise, or would be addressing a health care professional. This is so that the assistant is not a response, but is proactive in assisting users resolve stress in the right way before its develops into a serious problem. The AI-powered voice assistant operates based on real-time data processing, which ensures sustaining real-time data and communication. Deep learning was applied methods, i.e., CNN-based face recognition improves the accuracy of measurement of the stress level by identifying and interpreting brief micro-expressions, that can convey underlying tension even in the absence of overt verbal cues. Second, the integration of biometric sensors offers informative physiological data that augments facial expression analysis, thereby developing a multimodal stress assessment system. With Ongoing learning based on user input and adjustment of feedback accordingly. the assistant gets better over time, being precise and more specific to stress management solutions. The model is well-trained and validated in an effort to make it very precise and readable by many different people, environments, and lighting conditions. Among the most significant benefits of the system are privacy-enabling architecture and scalability.Unlike cloud-data storage-dependent centralized stress monitoring systems, this mobile AI assistant works offline on data without violating user privacy. With through the use of fewer remote servers, the system avoids loss of data and unauthorized use, thus being a secure and stealthy way of personal stress management. For enhanced performance, the system employs data augmentation technology. techniques that improve the CNN model. The application of variations in lighting, angles, and facial expressions, the model must identify stress cues for various conditions and thus suitable to use. Experimental result shows that the system works very well with very high accuracy in training and validation stage, which implies that it can generalize to new data.

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