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ABSTRACT

This project presents a real-time stress detection and management system that aims to promote mental wellness.

Existing research in stress detection often relies on isolated physiological signals or facial analysis. However, the combination of both has shown potential for more reliable results.

Our system integrates facial emotion detection using Convolutional Neural Networks (CNNs) with Electrodermal Activity (EDA) sensors, interfaced through an ESP32. The data is sent to Firebase and visualized via a React-based web application offering remedies like music and relaxation exercises.

The results confirm improved stress identification through multimodal input.

Future work includes wearable integration and expanded therapeutic interventions.

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LIST OF ABBREVIATIONS

Sl.No	Abbreviations	Keywords
1	GSR	Galvanic Skin Response
2	ML	Machine Learning
3	KNN	K Nearest Neighbours
4	IOT	Internet Of Things
5	EDA	Electrodermal Activity
6	CNN	Convolutional Neural Network
7	FCN	Fully Convolutional Network
8	SVM	Support vector Machine
9	RF	Random Forest

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CHAPTER - 1

INTRODUCTION

Stress is now a common occurrence in daily life. Understanding and managing it is more important than ever to preserve your happiness and well-being. Long-term stress can lead to serious problems like heart disease, low energy, and anxiety. People can manage stress before it has a detrimental effect on their health and well-being when they recognize it early.

There are several methods to detect stress, including tracking physiological changes like heart rate and skin reactivity or analyzing feelings and behaviors. Machine learning has opened up new avenues for stress identification by analyzing facial expressions and body language.

This system assesses emotions from both live and previously captured facial pictures using algorithms such as Random Forest, K-Nearest Neighbors, Support Vector Machines, and Convolutional Neural Networks. By examining facial expression patterns to identify whether a person is worried, these models offer accurate insights into their emotional state.

To further improve its reliability, the system also incorporates data from skin conductance, electrodermal activity, and heart rate. EDA measures the amount of perspiration that occurs when a person's skin reacts to stress. An ESP32 microcontroller with built-in sensors is used to collect this data in real-time and combine it with the emotion-based results. These inputs work together to create a clearer and more accurate picture of the stress level.later Create an app for individualized stress management by combining emotions and GSR data to identify stress levels.

This approach employs machine learning to provide users with a simple and efficient method of identifying and managing stress by combining insights from physiological signals and facial emotions. It gives them the tools to live a more balanced and healthful life by assisting them in understanding their stress levels and pointing them in the direction of easy ways to feel better.

1.1 Physiological Monitoring:

Stress immediately alters physiological signals, and these changes are tracked using a variety of techniques. Typical techniques include:

- Skin Conductance (also known as Galvanic Skin Response, or GSR): Stress can alter skin conductance by increasing the activity of sweat glands. This method is frequently used to measure arousal levels.
- Heart Rate Monitoring: An elevated heart rate is frequently the result of stress. Photoplethysmography (PPG) and electrocardiography (ECG) are used by devices like wearable fitness trackers and chest straps to measure changes in heart rate and heart rate variability (HRV), which are important markers of stress levels.
- Monitoring Respiratory Rate: Stress can change how people breathe, usually making them shallower and faster. To track these changes, monitoring devices employ wearable patches, spirometers, or chest straps.
- Blood Pressure: Stress frequently results in brief increases in blood pressure. Stress-related changes can be detected with the use of wearable cuffs or cuffless devices that use pulse transit time (PTT).
- Skin Temperature: Vasoconstriction during stress can cause the peripheral skin temperature to drop. Wearable temperature sensors or infrared thermometers can track these variations.
- Pupil Dilatation: When the autonomic nervous system is activated in response to stress, the size of the pupil may change. These changes can be detected by specialized cameras or eye-tracking devices.
- Muscle Activity (Electromyography, EMG): EMG sensors applied to particular muscle groups, like the forehead or shoulders, can measure muscle tension, which is exacerbated by stress.

- Electroencephalography (EEG) of the Brain Activity: Stress can change the patterns of brainwaves. These changes are measured by EEG devices, which offer a comprehensive understanding of emotional and cognitive reactions.
- Salivary Cortisol: Salivary cortisol levels can be obtained non-invasively and analyzed as a trustworthy biomarker of stress.

CHAPTER - 2

LITERATURE REVIEW

Table 2.1 An overview of the literature survey to identify the gaps

Sl.No.	Paper Title	Author	Year	Key Points
1	UBFC-Phys: A Multimodal Database For Psychophysiological Studies of Social Stress ,IEEE	Rita Meziati Sabour, Yannick Benezeth, Pierre De Oliveira, Julien Chappé, and Fan Yang.	2021	Deals with the social stress, bringing together physiological signals like heart rate, GSR, and EEG. It's designed to help develop machine learning models for detecting stress and recognizing emotions.
2	A Review on Mental Stress Detection Using Wearable Sensors and Machine Learning Techniques. IEEE.	Bakker J, Pechenizkiy, M,&Sidorova, N.	2021	Wearable sensors and machine learning for stress detection focus on heart rate, skin conductance, and brain activity, tackling dataset and feature extraction challenges.

3	Portable and wearable real-time stress monitoring: A critical review," Sensors and Actuators Reports,	O. Parlak	2021	Portable and wearable devices for real-time stress monitoring focus on sensors and techniques for continuous stress detection.
4	A New intelligent Approach for Automatic Stress Level Assessment Based on Multiple Physiological Parameters Monitoring	G. Ribeiro, O. Postolache, and F. F. Martín	2024	The system uses ESP32 microcontrollers to gather data from PPG, GSR, and temperature sensors, estimating key health metrics like heart rate, heart rate variability, respiratory rate, and SpO2. This data can be stored either locally or remotely on Firebase using Wi-Fi.
5	Emotion and Stress and Utilizing Galvanic Skin Response and Wearable Technology: A	Hosseini, R. Fang,R.Zhang, S.Rafatirad, andH.Homayoun,	2023	Develops a real-time emotion recognition system using GSR signals, processing and

	Real-time Approach for Mental Health Care,			classifying emotions with machine learning.
6	A Review on Mental Stress Detection Using Wearable Sensors and Machine Learning Techniques	S. Gedam ,S Paul	2021	Wearable sensors (ECG, EEG, GSR) combined with machine learning, sensor fusion, and deep learning enable real-time stress detection with improved accuracy across various environments.
7	Review of Stress Detection Methods using wearable sensors	G.Taskasaplidis, D. Fotiadis, and P. D. Bamidis		Focusing on wearable technologies and biological signals to assess stress through autonomic nervous system and HPA axis responses.
8	Real-Time Stress Detection and analysis using facial emotion recognition	H P Chandika ,B Soumya ,B N E Reddy	2024	Real-time stress detection is achieved through facial emotion recognition, analyzing

		and B M S S Manideep		facial expressions as non-invasive indicators for assessing psychological states.
9	Stress Detection with Machine Learning and Deep Learning using Multimodal Physiological Data	P Bobade ,M Vani	2020	Combines machine learning and deep learning to detect stress using multimodal physiological data (ECG, GSR, respiration rate), improving accuracy through data integration.
10	Extraction of facial features as indicators of stress and anxiety	M Pediaditis et al	2015	A method to assess stress and anxiety levels by analyzing facial expressions through computer vision, using facial cues as non-invasive indicators of psychological states.

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11	Using Deep Convolutional Neural Network for Emotion Detection on a Physiological Signals Dataset	L.Santamaria-Granados, M. Munoz-Orgaero,G.Ramirez-González, E. Abdulhay, and N. Arunkumar	2019	Uses the AMIGOS dataset and integrates ECG and GSR data to enhance emotion recognition, outperforming traditional machine learning approaches.

CHAPTER - 3

METHODOLOGY

3.1 Software Methodology

A facial emotion recognition model was developed using the CK+ dataset, which contained a total of 989 images—735 for training and 246 for testing. These images were used to detect seven different emotions: happiness, fear, sadness, contempt, anger, surprise, and disgust.

Multiple algorithms were evaluated for emotion detection, including Convolutional Neural Networks (CNN), K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Random Forest. Among these, CNN demonstrated the highest accuracy due to its ability to extract both local and global features through convolutional, pooling, and dense layers.

The model was implemented in Google Colab using TensorFlow and Keras. To ensure optimal performance, the dataset was pre-processed before training. Grayscale conversion was applied to simplify the images by removing color information. All images were resized to a standard dimension of 48x48 pixels to maintain uniformity. Normalization was performed to scale pixel values to the range [0, 1]. Label mapping was conducted to group the emotions into broader categories such as positive, negative, and neutral. The dataset was then split into training and testing sets in a 75:25 ratio.

Overfitting and underfitting were examined for each algorithm to ensure the generalization capability of the models and avoid performance degradation on unseen data.

3.1.1 Algorithms

3.1.1.1 Convolutional Neural Network (CNN)

Images were loaded from subfolders, each representing a specific emotion. After undergoing preprocessing, the images were label-encoded into categories: positive, negative, and neutral.

The CNN architecture consisted of an input layer that accepted 48x48 grayscale images, followed by four convolutional layers with increasing filter sizes (32, 64, 128, 156) to extract facial features. ReLU activation was applied to introduce non-linearity and enable the recognition of complex patterns. Pooling layers were used to reduce spatial dimensions. The 2D feature maps were then flattened into a 1D vector and passed through dense layers. Dropout regularization was applied to prevent overfitting.

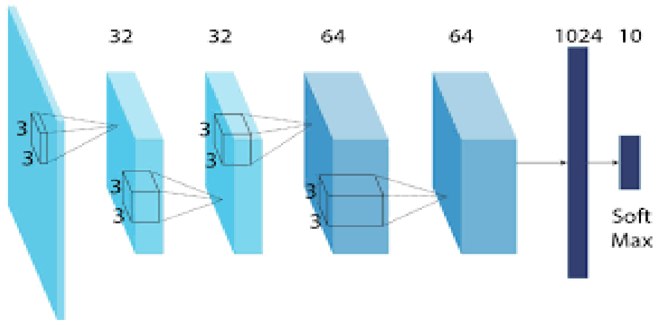

Fig 3.1 CNN model Architecture with four layers

30 To evaluate the performance of the stress detection model, standard classification metrics such as Accuracy, Recall, and F1 Score are used.. The formulas are given below:

A. Recall: How many of the actual labels are correctly predicted.

$$Recall = \frac{True\ Positives(TP)}{False\ Negatives(FN) + True\ Positives(TP)} \quad (1)$$

B. F1 score: A balance between precision and recall.

$$F1 - Score = 2\frac{Precision\ x\ Recall}{Precision + Recall} \quad (2)$$

C. Accuracy: The overall percentage of correct predictions

$$Accuracy = \frac{True\ Positives(TP) + True\ Negatives(TN)}{Total\ Samples} \quad (3)$$

D. Precision: How many of the predicted labels are correct.

$$Precision = \frac{True\ Positives(TP)}{False\ Positives(FP) + True\ Positives(TP)} \quad (4)$$

Overall the accuracy of CNN was 0.99.

Table 3.1.1 CNN algorithm performance metrics

	Accuracy	Recall	F1-score
Negative	1.00	1.00	1.00
Positive	0.97	1.00	0.99
Neutral	1.00	0.99	0.99

3.1.1.2 Support Vector Machine (SVM)

Support Vector Machine (SVM) maps input data into a higher-dimensional space where classes can be linearly separated. Images were loaded from subfolders based on their respective emotions and underwent preprocessing, including grayscale conversion, resizing to 48x48, and normalization. Label mapping was done to categorize emotions as positive, negative, or neutral.

The images were reshaped into 1D arrays and label-encoded into numeric values. A 75:25 train-test split was applied. SVM, primarily used for classification, employed the Radial Basis Function (RBF) kernel to create non-linear decision boundaries by measuring data point similarity.

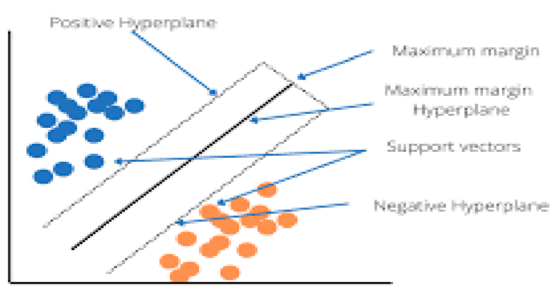

Fig 3.2 SVM model

Key hyperparameters included C, which controls the trade-off between margin size and classification error, and gamma, which determines the influence of individual data points. After prediction, numeric labels were decoded back to their corresponding emotion categories for evaluation.

Table 3.1.2 SVM algorithm performance metrics

	Accuracy	Recall	F1-score
Negative	0.98	0.83	0.90
Positive	0.96	0.99	0.97
Neutral	0.88	0.94	0.99

SVM model showed an accuracy of 0.94.It performed but it slightly lags compared to CNN.

3.1.1.3 Random Forest

Random Forest is an ensemble learning algorithm that combines predictions from multiple decision trees. Each tree is trained on a randomly sampled subset containing approximately 63.2% of the original data. At each node split, a random subset of features is selected. If M is the total number of features, then only a subset of M is used for each split.

$$m = \sqrt{M}(for\ classification\ tasks) \tag{5}$$

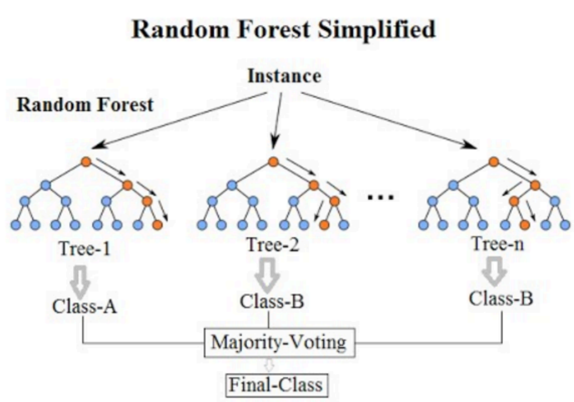

Figure 3.3 Random Forest model

After feature extraction, each decision tree recursively partitions the data by selecting splits that maximize the reduction in impurity. Gini Impurity is used as the splitting criterion and is defined as:

$$Gini(t) = 1 - \sum_{i-1}^{c} p_i^2 \tag{6}$$

where *pi* is the proportion of samples belonging to class *i* at node *t*, and *C* is the number of classes.

For final classification, a majority voting mechanism is applied across all trees:

$$\hat{y} = arg\,max_c \sum_{j=1}^{T} I(y_j = c) \tag{7}$$

Table 3.1.3 Random Forest algorithm performance metrics

	Accuracy	Recall	F1-score
Negative	0.98	1.00	0.99
Positive	0.98	1.00	1.00
Neutral	1.00	0.92	0.99

Random forest gave an accuracy of 0.99. Random forest and CNN are showing good accuracy but extracting facial features is done more precisely by CNN .

3.1.1.4 K-Nearest Neighbors (KNN)

K-Nearest Neighbors (KNN) classifies images based on their similarity to nearby samples in the training data using Euclidean distance. Preprocessing steps such as grayscale conversion, resizing, normalization, and label encoding were applied. Images were flattened into 1D arrays, and the dataset was split into training and testing sets in a 75:25 ratio. Label encoding was consistent across all algorithms: Positive = 0, Negative = 1, Neutral = 2.

The model stores data points and, during prediction, compares new samples with stored ones. Here, *k = 3* was chosen, meaning the prediction was based on the three nearest neighbors. The distance between data points was calculated using the Euclidean distance formula:

$$Distance(Xi, Xj) = \sqrt{\sum_{k=1}^{n} (X_{ik} - X_{jk})^2} \tag{8}$$

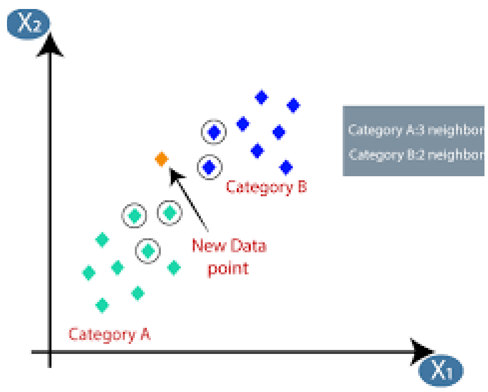

Figure 3.4 KNN model

Table 3.1.4 KNN algorithm performance metrics

	Accuracy	Recall	F1-score
Negative	0.81	0.66	0.83
Positive	0.95	0.78	0.94
Neutral	0.87	0.67	0.88

KNN achieved an overall accuracy of 0.89, but showed lower recall values, indicating a limitation in correctly identifying all true positives.

3.1.2 Overall

Among all evaluated algorithms—CNN, SVM, Random Forest, and KNN—CNN outperformed the others due to its ability to accurately extract facial features through its layered architecture. This makes CNN the most suitable model for facial emotion recognition. Using this CNN model, emotions can be identified effectively, aiding in stress level assessment based on detected emotional states.

3.2 Hardware And Software Implementation

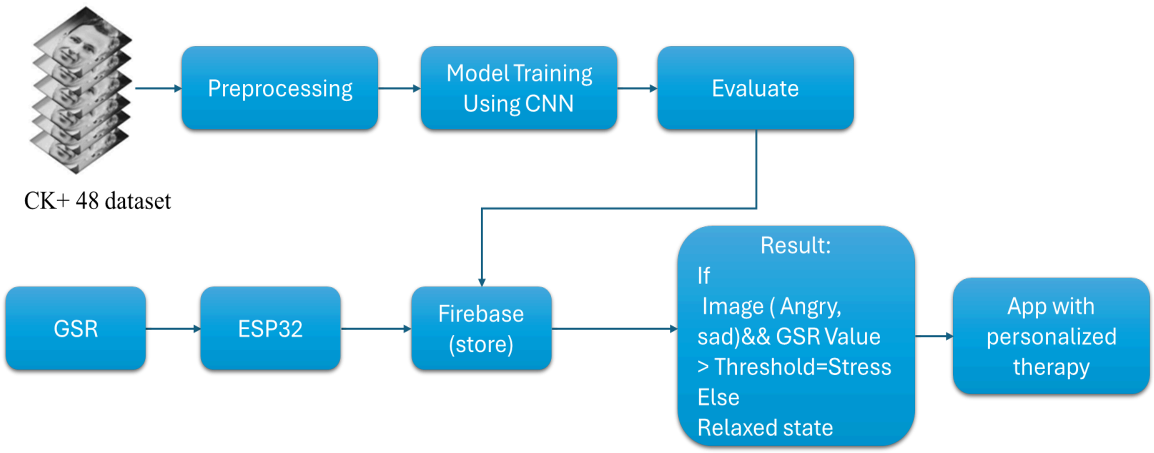

Figure 3.5: Block diagram

3.2.1 Emotion Recognition Using Facial Features[Software]

3.2.1.1 Environment Setup

Install Necessary Libraries

To set up the Python environment:

1. Installed the required libraries using pip

Set Up VS Code

1. Open Visual Studio Code (VS Code).
2. Created a new Python file
3. Provided code into the file.
4. Provided the Python interpreter in VS Code to the version where the required libraries are installed.

Hardware Requirements

1. The system has a functional webcam for live capture.
2. Tested the webcam.

3.2.1.2 Image Upload and Stress Classification

Run the Script

Execute the script in the VS Code terminal

Upload Image

1. When prompted, a file dialog will appear to let you upload an image.
2. Selected an image containing a face for emotion analysis.

Emotion Classification

1. The script:
    - Detects faces using the Haar cascade classifier.
    - Analyzes emotions using DeepFace.
    - Maps emotions:
        - angry, sad→ classified as stress.
        - happy, surprise → classified as themselves.
        - fear, disgust → classified as themselves.

Result Visualization

1. The processed image is displayed in a new window showing:
    - A rectangle around the detected face.
    - A label with the predicted emotion or stress classification.

3.2.1.3 Stress Detection Using Webcam

Modified the Code for Live Capture

Added a function for webcam input

Run Live Detection

1. Replaced the upload_image() call with live_capture_and_predict() in the main() function for detection.
2. Executed the script to display the live webcam feed.

3.2.1.4 Combining and Testing

Switch Between Modes

1. Added an option for users to choose between image upload or live capture

Run the Updated Script

Execute the script and choose the desired mode:

1. Option 1: Upload an image for analysis.
2. Option 2: Use live capture for detection.

3.2.1.5 Validation and Debugging

Validation

1. Tested the script with various images and live feeds to ensure:
    - Correct stress classification for emotions (angry, sad, fear, disgust).
    - Accurate identification of non-stress emotions (happy, surprise).

Debugging

1. Common issues to address:
    - No Face Detected: Ensure proper lighting and visible faces in the image or live feed.
    - Incorrect Classification: Reviewing preprocessing steps and considering improving the DeepFace model configuration.

3.2.2 Stress Detection Using EDA sensor

1. ESP32:

   The ESP32-WROOM-32 is a compact and versatile microcontroller designed for IoT applications. With its dual-core processor, built-in Wi-Fi, and Bluetooth capabilities, it efficiently handles data processing and communication in real time. In this project, the ESP32 serves as the central hub, collecting physiological data from sensors, running a lightweight stress detection model, and transmitting results to the mobile app. Its small size, low power consumption, and flexibility make it ideal for wearable stress monitoring and intervention systems.

2. EDA sensor:

The GSR sensor measures changes in the skin's electrical conductivity, which occur due to sweat gland activity influenced by stress levels. When stress increases, the sensor detects the subtle rise in conductance and provides an analog signal for analysis. In this project, the GSR sensor plays a crucial role in monitoring physiological stress responses in real time. Its integration with the ESP32 ensures accurate and timely stress detection, forming the backbone of the system's real-time stress monitoring capabilities.

3.2.2.1 System Setup and Initialization

1. Hardware Components:
   - Using an EDA sensor connected to an ESP32 microcontroller to measure electrodermal activity.
   - The GSR values from the EDA sensor indicate skin conductivity, which correlates with stress levels.
2. Wi-Fi Configuration:
   - Connect the ESP32 to a Wi-Fi network by specifying the WIFI_SSID and WIFI_PASSWORD.
   - Ensure the ESP32 has a stable Wi-Fi connection .
3. Firebase Setup:
   - Configure Firebase Database to store GSR data.
   - Use the provided Firebase credentials (FIREBASE_HOST and FIREBASE_AUTH) to authenticate and initialize Firebase communication.
4. EDA Sensor Pin:
   - Connect the EDA sensor to the specified analog pin (GSR_PIN 34).

3.2.2.2 Data Collection and Processing

1. Data Reading:
   - Collect 20 consecutive readings from the EDA sensor using analogRead(GSR_PIN).
2. Averaging GSR Values:

- Compute the average of the collected GSR values to reduce noise and fluctuations in the readings.

3. Threshold Determination:
   - Define a threshold value for classifying stress.
   - Compare the average GSR value to this threshold:
     - Above Threshold: Stress detected.
     - Below Threshold: Relaxed.

3.2.2.3 Uploading Data to Firebase

1. Real-Time Storage:
   - Use Firebase to store the averaged GSR values along with a unique timestamp-based path.
2. Error Handling:
   - Implement robust error checking for Firebase operations to ensure data reliability.
3. Testing:
   - Validate the successful upload of GSR values by monitoring Firebase entries.

3.2.2.4 Stress Classification

1. Threshold-Based Classification:
   - The threshold logic for stress detection is currently implemented on the ESP32.
2. Integration with Software:
   - The classification logic for combining GSR data and emotion detection will be handled in the software.
   - This integration is under development and will involve syncing EDA sensor data with emotion detection models.

3.3 Web Application Methodology

The web application serves as the main interface for users to interact with the stress detection and management system. It is built using React.js, a popular JavaScript framework known for its simplicity and ability to create dynamic, interactive user interfaces. The goal of this application is to fetch real-time data from a Firebase database, assess the user's stress level, and provide meaningful feedback and resources to help them relax and feel better.

3.3.1 Setting Up the Environment

To start, the app connects to Firebase, which acts as a cloud backend. We initialize Firebase using the provided configuration and use it to pull live data such as GSR (Galvanic Skin Response) readings and facial emotion classification which is uploaded by the ESP32 microcontroller and an emotion detection system.

Firebase allows the app to listen for changes as they happen, meaning any updates (like a sudden spike in stress) immediately reflect on the user interface without needing to refresh the page.

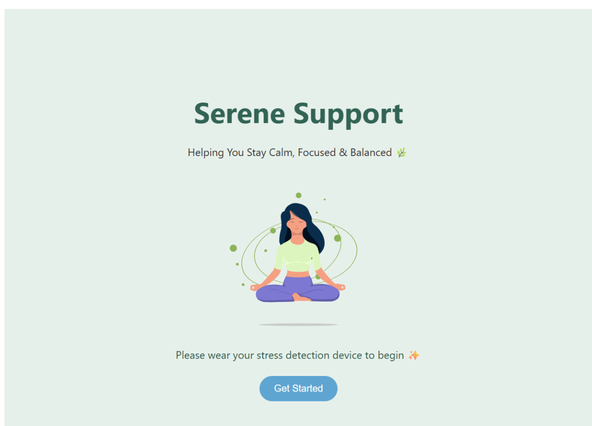

Figure 3.6 : Home screen

3.3.2 How It Reads and Uses the Data

The app keeps track of key pieces of information:

- The user's GSR value, which reflects their stress level.
- Their emotion label, such as "Relaxed" or "Stressed".

- Basic user details like name and age.

When the app detects a high GSR value and a stressed facial expression, it responds by showing calming suggestions and resources. If the user seems calm, it provides positive reinforcement to keep them motivated.

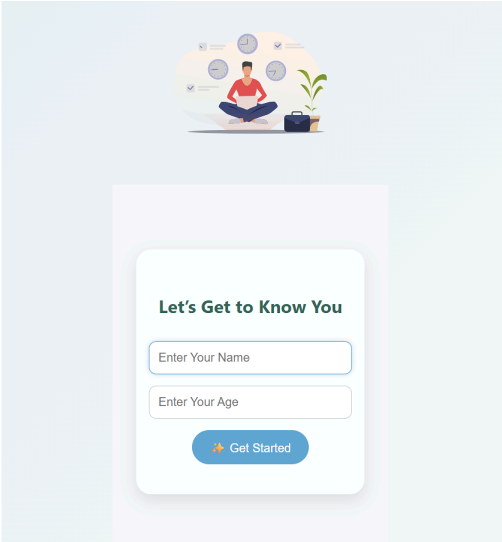

Figure 3.7 : User information page

3.3.3 Real-Time Stress Detection Logic

We set a threshold for GSR (e.g., values above 1800). If the GSR is high and the emotion is tagged as "stress," the app assumes the user is feeling overwhelmed. It then switches the view to show various relaxation methods, including yoga, meditation, soothing music, and helpful lifestyle suggestions like connecting with nature or pets.

3.3.4. Engaging and Helpful UI

To make the app more engaging, we use Lottie animations lightweight, visually appealing animations that play in real-time. These animations show peaceful scenes, like someone meditating or walking outdoors, and they enhance the overall user experience.

The app also greets users personally (e.g., "Hi, Alice!") and guides them gently through the process, from entering their name and age to choosing an activity that suits their mood.

3.3.5. Curated Wellness Content

If the system detects stress, the app presents a carefully chosen list of YouTube videos related to:

- Yoga sessions
- Guided meditations
- Relaxing music

These links are displayed in a simple, easy-to-navigate list format, making it effortless for users to try them out immediately.

3.3.6. Clean Design and Smooth Interaction

We've kept the interface light, soothing, and distraction-free. The CSS ensures that:

- The layout adapts to different screen sizes
- Input forms are user-friendly
- Colors and transitions are gentle, in line with the calming theme

Buttons are clearly labeled, and forms are designed to make users feel at ease while using the app.

3.3.7. Built to Scale

The app uses reusable components, meaning new features can be added easily without starting from scratch. For example, more stress-relief methods, user tracking, or even chatbots could be added in the future.

The code is also modular and clean, following best practices for React development. This makes it maintainable and ready for upgrades as the system grows.

CHAPTER - 4

RESULTS AND DISCUSSION

4.1 Result for Training algorithms on a facial emotion dataset

Table 4.1 Comparison of Different Algorithms with their Performance Metrics

Algorithm	Metric	Negative	Positive	Neutral
CNN	Precision	1.00	0.97	1.00
	Recall	1.00	1.00	0.99
	F1 score	1.00	0.99	0.99
KNN	Precision	0.81	0.95	0.87
	Recall	0.66	0.78	0.67
	F1 score	0.83	0.94	0.88
SVM	Precision	0.98	0.96	0.88
	Recall	0.83	0.99	0.94
	F1 score	0.90	0.97	0.99
Random Forest	Precision	0.98	1.00	1.00
	Recall	1.00	1.00	0.92
	F1 score	0.99	1.00	0.99
FCN	Precision	0.00	0.96	0.53
	Recall	0.00	0.97	0.95
	F1 score	0.00	0.96	0.68

CNN and Random Forest are the top-performing algorithms.

- SVM performs well but slightly lags behind.
- KNN shows moderate performance, struggling with recall for certain classes.
- FCN fails significantly in classifying Negative and Neutral categories.
- CNN or Random Forest are recommended for deployment.

4.2 Results for Hardware and Software Implementation

4.2.1 Software Implementation

A trained model along with the DeepFace module was used to detect faces and identify emotions. Emotions such as 'angry' and 'sad' were classified as stress indicators, while other emotions remained in their original categories.

Fig 4.1 Image with angry and sad emotion classified as stress

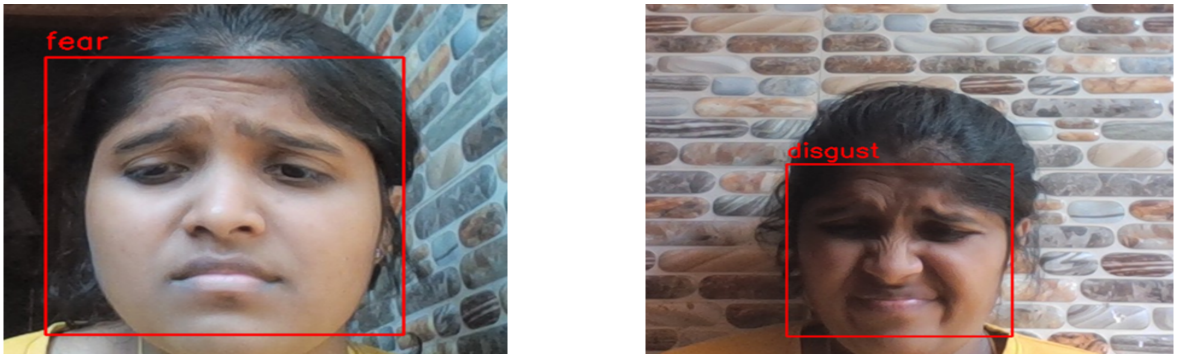

Fig 4.2 Images with fear and disgust emotions

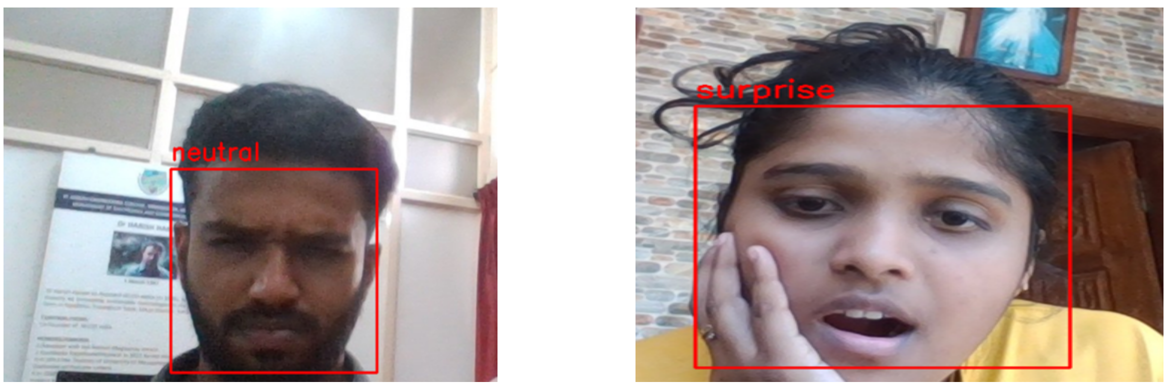

Fig 4.3 Images with neutral and surprise emotions

Fig 4.4 Image with happy emotion

4.2.2 Hardware Implementation

The GSR-based stress detection system successfully monitored and processed skin conductance data to identify stress levels. The average GSR values were calculated over 20 readings, and the system classified the user as either "Relaxed" or "Stressed" based on a predefined threshold of 2000.

- Relaxed State: GSR Average below 2000.
- Stressed State: GSR Average equal to or above 2000.

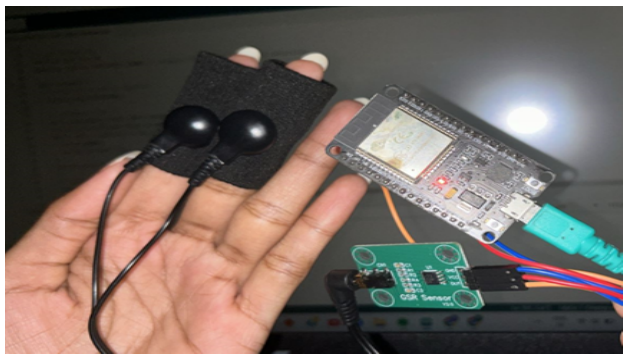

Fig 4.5 Hardware implementation

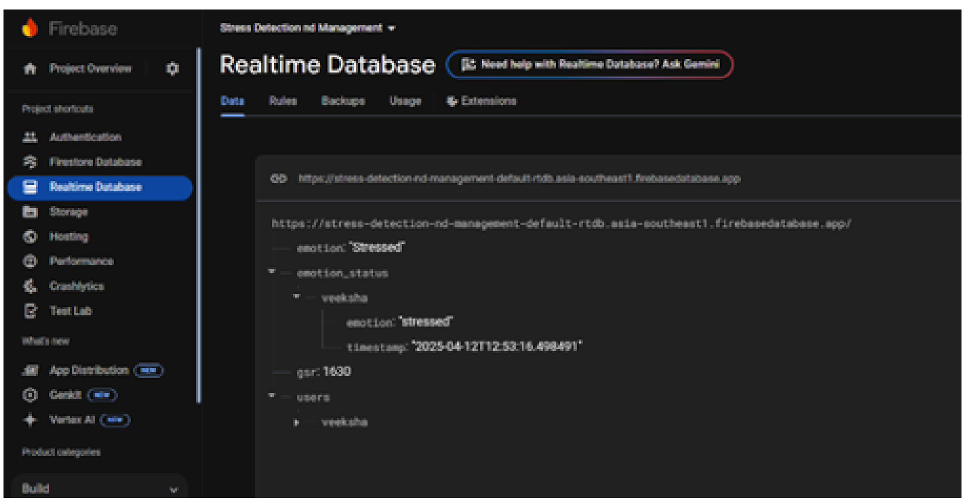

Fig 4.6 GSR Data Visualization in Firebase Realtime Database

4.2.3 Emotion and GSR-Based Stress Feedback System

The Emotion detection outputs with the EDA sensor data through firebase is synced and Based on the analysis.

The below mentioned is the overview of the Web application:

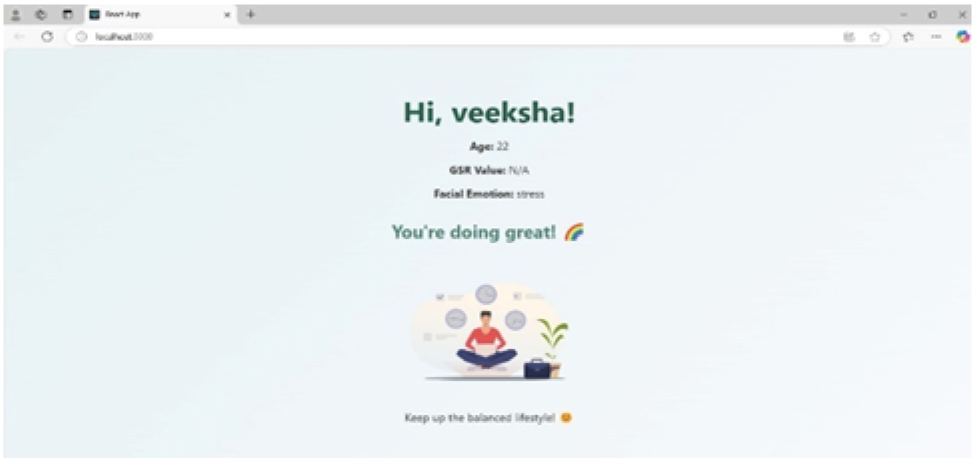

Figure 5.4. Home Page view of the Web Application

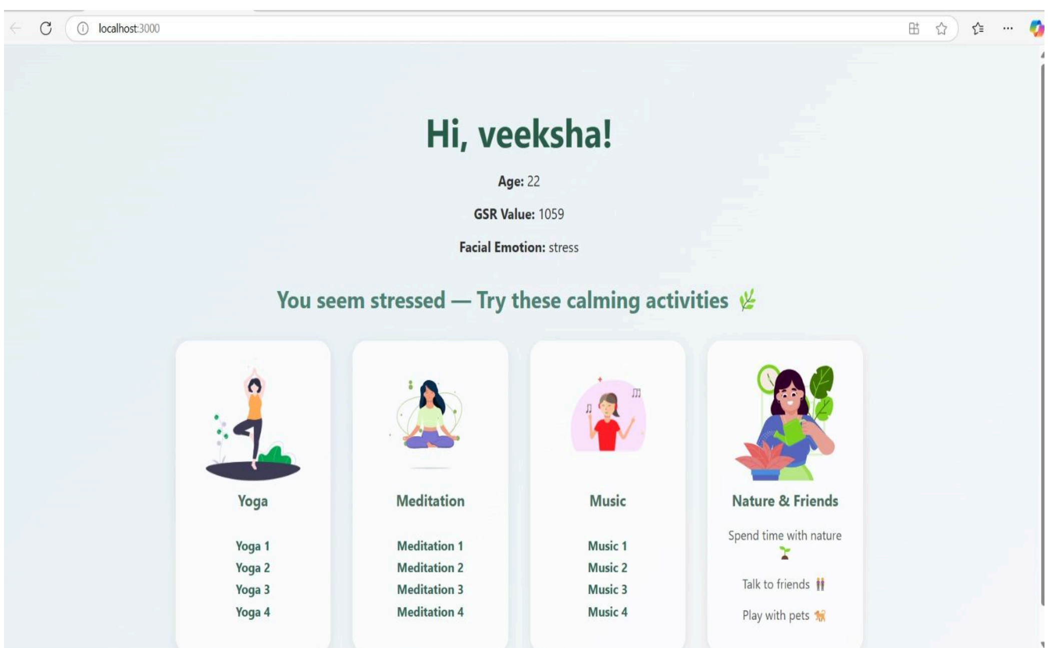

Figure 5.5 Image demonstrating the working of App

The application detects stress by combining facial emotion analysis and GSR sensor values. When stress is identified, the application displays calming activity suggestions like yoga, meditation, music, and spending time with nature or friends.

CHAPTER - 5

CONCLUSION

This project presents a practical approach to stress detection and personalized intervention by combining facial emotion recognition with physiological signals. By integrating data from facial expressions and EDA measured via a GSR sensor, the system shows a more complete understanding of a person's emotional and physical state. Using machine learning models, especially Convolutional Neural Networks (CNN) the system can accurately identify stress-related emotions such as anger and sadness, while the ESP32-based GSR sensor provides real-time physiological insights.

What sets this work apart is the integration of emotion detection, sensor data, and cloud storage via Firebase to offer timely and personalized stress-relief suggestions through a web application. Whether it's recommending yoga, meditation, or calming music, the system ensures that the user receives support that suits their individual needs in that moment.

Stress is increasingly common thus this project shows how technology can be used thoughtfully not just to detect stress, but to respond with care. It shows accessible, user-friendly tools that improve individuals to take control of their mental well-being, offering both early detection and immediate support in one integrated platform.

CHAPTER - 6

FUTURE SCOPE AND IMPLICATIONS

The project system has a lot of room to grow in the future. Using more sophisticated machine learning algorithms and incorporating other data modalities, like voice analysis and physical activity levels, can improve its accuracy. These enhancements might offer a more thorough comprehension of stressors.

Additionally, the system can develop to provide individualized interventions based on a person's stress profile, such as breathing exercises, mindfulness exercises, or relaxation techniques. Optimizing the hardware and software elements could make the solution more affordable, portable, and available to a wider range of users. It could also integrate with wearable technology, such as fitness trackers or smartwatches.

Long-term stress monitoring is another potential use for the system, which would allow users to pinpoint stressors and modify their lifestyles.It could be a useful tool for counselors and therapists, giving them insight into their clients' feelings and enhancing the effectiveness and personalization of therapy.

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APPENDIX

LIST OF COMPONENTS USED FOR PROJECT

SL.NO.	COMPONENT	VALUE	DETAILS
1	GSR Skin Current Sensor	3.3V	Measures skin conductivity to assess stress levels
2	ESP32 wroom-32	3.0 V ~ 3.6 V	Microcontroller with Wi-Fi and Bluetooth capabilities for IoT applications.

LIST OF SOFTWARE TOOLS USED FOR THE PROJECT

SL.NO.	SOFTWARE	VERSION/ DETAILS
1	Arduino IDE	2.3.4 / It is used for programming and uploading code to the ESP32.
2	Visual Studio Code	1.93 / Used as a code editor for more complex development tasks.
3	Firebase	A cloud platform used in data storage, authentication and real-time database functionality.