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SENSOR BASED EMOTIONAL RECOGNITION IN FACE USING CNN

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ABSTRACT

This research paper introduces a smart system designed to detect and monitor early signs of depression using advanced sensors connected to an Internet of Things (IoT) device. Depression is a widespread mental health issue that can impact daily life and physical well-being, leading to symptoms like confusion, fatigue, and pain. The system employs sensors such as the Nano Bio Sensor and pulse sensor to track changes in heart rate and other body signals, which may indicate mood swings or depressive states. When these signs are identified, the system sends alerts to caregivers or healthcare providers, enabling timely support and monitoring treatment effectiveness. This innovative approach aims to enhance outcomes for individuals dealing with depression by offering proactive and personalized monitoring solutions.

KEYWORDS:- *Smart system, Depression, Advanced sensors, Internet of Things (IoT) device, Nano Bio Sensor, Pulse sensor, Heart rate, Body signals, Depressive states.*

1. INTRODUCTION

Sensor-based emotion recognition in faces using Convolutional Neural Networks (CNNs) is a cutting-edge field at the intersection of computer vision and affective computing. By leveraging data from various sensors, such as cameras and depth sensors, combined with CNN architectures, researchers aim to accurately detect and classify human emotions based on facial expressions. CNNs are particularly effective in this task as they can automatically learn and extract relevant features from raw sensor data, allowing for robust and efficient emotion recognition. This technology holds immense potential for applications in diverse domains, including human-computer interaction, healthcare, and marketing, paving the way for more personalized and empathetic technological systems. By integrating sensor data, we aim to enrich the emotional understanding captured from facial expressions, thus enhancing the system's performance across diverse real-world scenarios.

Furthermore, this research aims not only to recognize basic emotions like happiness, sadness, anger, and surprise but also to delve into nuanced emotional states, such as confusion or amusement, which are crucial in applications like affective computing and mental health monitoring.

2. Problem Statement and Motivation

In traditional mental health assessment, personalized recommendations for individuals with depression are lacking. Generic advice is often provided to all patients, neglecting their unique needs and preferences. To address these challenges, Emotion Net, a CNN-based model, specializes in emotion recognition from facial expressions.[1] Variability in Human Faces: Human faces vary significantly in shape, size, pose, expression, lighting, and makeup, making it challenging for algorithms to adapt to different conditions and scenarios.[2] Continuous Monitoring Requirement: Effective depression monitoring requires continuous collection and analysis of diverse data streams such as heart rate, sleep patterns, physical activity, social interaction, and environmental triggers.[3] Facial Recognition System Challenges: Implementing a facial recognition system for depression monitoring faces obstacles like variable lighting conditions, varying camera qualities, and uncontrolled environments.[4] Accuracy Challenges in Emotional Recognition: Existing systems struggle to achieve consistent high accuracy in emotional recognition.[5] Variabilities in individual facial expressions, physiological responses, and the dynamic nature of emotions present significant hurdles. Developing a reliable system that accurately interprets subtle emotional cues remains a critical problem.[6] Ultimately, the motivation for deepening depression detection lies in our desire to alleviate suffering, improve mental health outcomes, and create a society where everyone has access to the support they need to thrive.

3. Literature survey

Researchers Mukherjee and Roy[1] developed a novel depression detection mechanism based on EEG signals, employing a feedforward neural network for classification and integrating a depression level indicator circuit.

Cana, Arnrich, and Ersoy[2] conducted a study exploring depression detection in daily life scenarios using smartphones and wearable sensors, categorizing works based on physiological modalities and targeted environments.

Alberdi, Aztiria, and Basarab[3] conducted a comprehensive review of automatic depression detection methods in office environments, examining measurements across psychological, physiological, and behavioral modalities.

Zhai and Barreto[4] developed a depression detection system relying on non-invasive physiological signals, utilizing Support Vector Machine for affective state classification.

Massot et al.[5] designed an ambulatory device for measuring heart rate, electrodermal activity, and skin temperature, specifically for objective depression evaluation.

Jeon, Bae, Lee, Jang, and Lee[6] proposed an innovative depression recognition algorithm using facial images and landmarks, implementing a deep neural network for efficient recognition.

Vandana, Marriwala, and Chaudhary[7] introduced a hybrid model for depression detection, combining textual and audio features through deep learning algorithms for comprehensive analysis.

Joshi[8] reviewed existing studies on Artificial Intelligence (AI) and Machine Learning (ML) techniques for depression detection, highlighting approaches using facial expressions, emotional chatbots, and social media text analysis.

Kim and Jang[9] proposed a framework for automatic depression detection using smartphone-based speech signals, focusing on large-scale acoustic characteristics for accurate diagnosis.

Liu, Feng, and Ahmed[10] utilized machine learning techniques to detect depression on social media, analyzing demographic characteristics and text sentiment to improve detection accuracy.

These studies contribute valuable insights into diverse methodologies and technologies for depression detection and emotional recognition, laying a strong foundation for further research in this field. Recent approaches mainly based on the deep learning algorithms and architectures.

4. METHODOLOGY

***Data collection*:** Physiological data is collected from sensors such as sweat, temperature, and heartbeat sensors. Facial expressions are captured and analyzed using AI algorithms through a laptop camera.

Categorization of depression: The project categorizes depression into three stages: normal, moderate, and severe based on the collected physiological data and facial expression analysis.

System operation: The central processing unit, represented by the STM32 microcontroller, manages data collection from sensors and oversees the overall system operation.

Real-time data feedback can be displayed on an LCD screen, providing immediate information to users.

Dataset collection: Begin by collecting a comprehensive dataset of facial images. This dataset should encompass a wide range of emotions, diverse demographics, and various environmental conditions to ensure the model's robustness and generalizability.

Data preprocessing: Clean and preprocess the facial images to enhance the model's performance. This may involve tasks such as resizing images to a standard size, normalizing pixel values, and applying techniques like data augmentation to increase the diversity of the dataset.

Feature extraction: Develop or select a CNN architecture suitable for extracting relevant features from facial images. CNNs are effective for this task due to their ability to automatically learn hierarchical representations of visual data.

Emergency response mechanism: In cases of severe depression, the system is programmed to send instant text message alerts to specified contacts for prompt assistance.

Intervention for moderate cases: For individuals categorized in the moderate stage of depression, the system delivers personalized suggestions to uplift mood and encourage early intervention.

Facial emotion detection: The system analyzes facial images using Haar Cascade, a machine learning object detection method, to identify faces within the images.

Preprocessing techniques are applied to refine the input data quality for accurate facial emotion detection.

Training neural network: A Convolutional Neural Network (CNN) is trained using a labeled dataset of facial images with associated emotion labels.

The CNN's weights are optimized based on the labeled dataset, enabling it to make precise predictions on new data without requiring retraining.

Workflow overview: The workflow comprises preprocessing of input images, face detection using Haar Cascade, and training a dedicated CNN for emotion recognition.

Advanced techniques: Post-training, advanced techniques such as multi-modal fusion, dynamic model adaptation, and privacy-preserving methods can be implemented to enhance system performance and user privacy. This methodology ensures a structured and efficient approach to detect depression early and provide appropriate support, integrating data analysis from physiological sensors with advanced facial emotion recognition technologies.

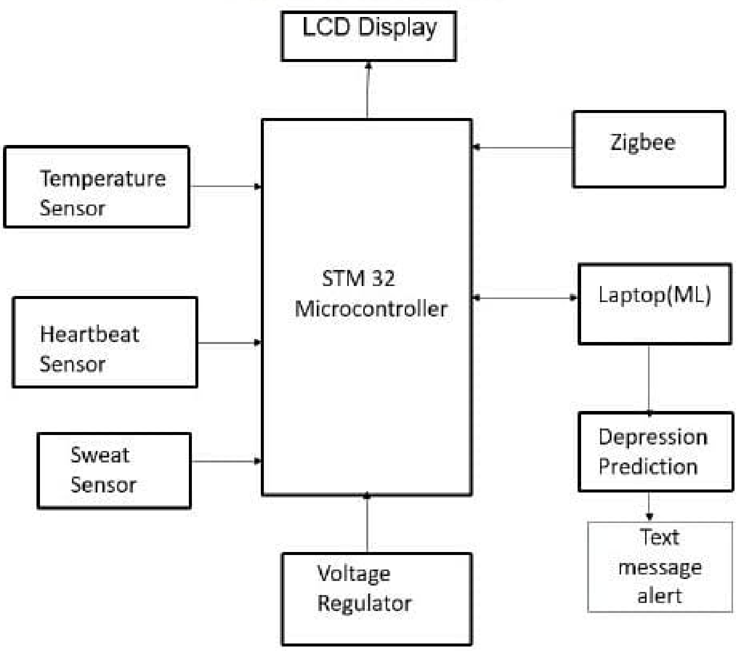

Fig. 1: Block diagram.

This system combines physiological data from sweat, temperature and heartbeat sensor with behavioral causes obtained from facial expressions recognition through a laptop camera.STM32 is a family of microcontrollers by STMicroelectronics. In this project, it serves as the central processing unit that collects data from various sensors, and controls the overall operation of the system. It collects data from sweat, temperature and heartbeat sensor along side AI analysis of facial expression recognition from a laptop camera providing a view of an individual emotional state. The microcontroller may also control the LCD display to show real-time data or feedback to the user in severe cases the system sends immediate text message alerts to specified contacts.

Model architecture

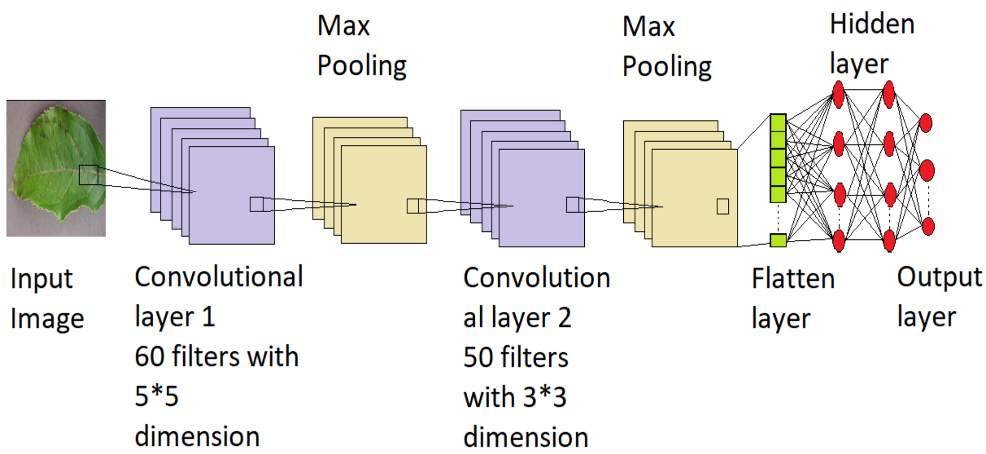

Fig. 2: Customized model architechture.

a. *Input layer*: The input layer, which accepts input pictures and extracts their pixel values, is the first layer of our CNN design. The basis for further processing and analysis is provided by this.

b. *Convolutional layers:* For the purpose of removing pertinent information from the input pictures, the CNN uses many convolutional layers. The layers provide feature maps that capture key object features using convolution with various kernels. For thorough feature extraction, our design uses a mix of filters in these levels. In order to efficiently capture different characteristics, the second convolutional layer includes a higher number of filters of different sizes than the first layer.

c. *Pooling layers:* Following the convolutional layers, pooling layers are very important for bringing down the dimensionality of the feature maps and network parameters. We downsample the feature maps while maintaining pertinent data using MaxPooling2D, a popular pooling approach. This process improves the computational effectiveness of the CNN and aids in the identification of dominating characteristics.

d. *Non-linear activation layers:* Rectified linear units (ReLU) are used as the activation function to provide nonlinearity and make feature categorization easier. ReLU transforms the input by removing negative values, which enables the CNN to efficiently capture complex feature patterns in the hidden layers.

e. *Fully connected layer:* The completely connected layer receives information from lower levels and creates direct connections between neurons in higher layers. This enables the network to take into account the general knowledge obtained from the convolutional layers and provide final predictions using the characteristics that were extracted.

f. *Normalization layer:* We propose a batch normalization layer in our CNN architecture. This layer ensures a uniform distribution of values by normalizing each channel over a small batch of data. This normalizing procedure increases he stability and performance of the model, which enhances generalization and prediction accuracy.

g. *Softmax layer:* We add a softmax layer to the CNN's conclusion in order to analyze the network's performance and provide significant findings. With the help of the softmax function, output values are converted into a probability distribution for several classes. As a result, we are able to assess the classifications made by the model with confidence and make accurate predictions.

5. Haarcascade alogrithm

The Haar Cascade algorithm, originally designed for object detection tasks like face detection, can be adapted for facial expression detection by training a custom Haar Cascade classifier. This involves collecting a labeled dataset of images showcasing various facial expressions such as happiness, sadness, anger, surprise, and others. Key features related to facial expressions, like changes in eyebrow position, mouth shape, eye openness, and overall facial muscle movements, are selected for training the classifier. The training process adjusts parameters iteratively to minimize false positives and negatives while maximizing detection accuracy. However, it's important to note that while Haar Cascades can provide basic facial expression detection capabilities, they may not match the accuracy of more advanced techniques such as deep learning-based models like CNNs, which excel at learning complex patterns and features directly from data. For robust and accurate facial expression detection, especially in real-world applications with diverse expressions and conditions, deep learning approaches are often preferred due to their superior performance.

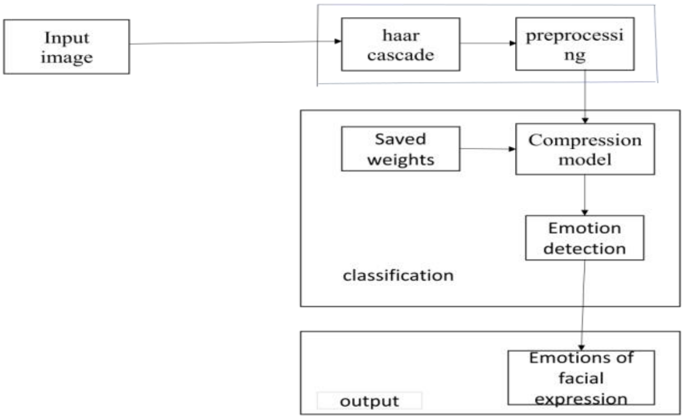

Fig. 2: Flowchart of haar cascade.

The input to your system is an image, likely a facial image in this context. Harr Cascade is amachine learning object detection method used to identify objects in images or video. In the context of facial emotion detection, it can be used to detect faces in the input image. Preprocessing is a crucial step in preparing the input data for the neural network. It involves various operations to enhance the quality of the input data. For facial emotion detection. Training a neural network involves adjusting its weights based on a labeled dataset. Once amodel is trained, the learned weights can be saved and reused for inference on new data. This helps to avoid the need to retrain the model each time it's used.

6. Dataset and Labelling

The FER2013 dataset is a widely used benchmark dataset for facial expression recognition research. It contains facial images labeled with one of seven emotions: anger, disgust, fear, happiness, sadness, surprise, and neutrality. The dataset was created by researchers at the Swiss Federal Institute of Technology (EPFL). the FER2013 dataset, which is a collection of facial expressions with labels. The FER2013 dataset is indeed commonly used for training Convolutional Neural Networks (CNNs) for facial emotion recognition tasks.

7. RESULT AND DISCUSSION

Emotional recognition using facial expressions involves algorithms that analyze facial features to identify emotions like happiness, sadness, anger, etc. These algorithms are employed in various fields, including psychology, marketing, and human-computer interaction. They rely on machine learning techniques to interpret facial expressions accurately.

When assessing our model, which is shown in Table I, the factors like happy, sad, neutral, angry, scared, disgust, surprise are taken such as temperature, heartbeat, sweat sensor.

Table 1: Evaluation our model using different sensors.

Facial Expression	*Temperature In Celsius*	*Sweat level*	*Heartbeat rate*
Angry	38	270mg/L	99 BPM
Happy	35.2	250mg/L	90 BPM
Neutral	35	260mg/L	110 BPM
Scared	35	290mg/L	120 BPM
Surprise	36.5	270mg/L	105 BPM
Sad	40	290mg/L	87 BPM

By using Think Speak allows individual to collect, analyze, and visualize live data streams in real-time.

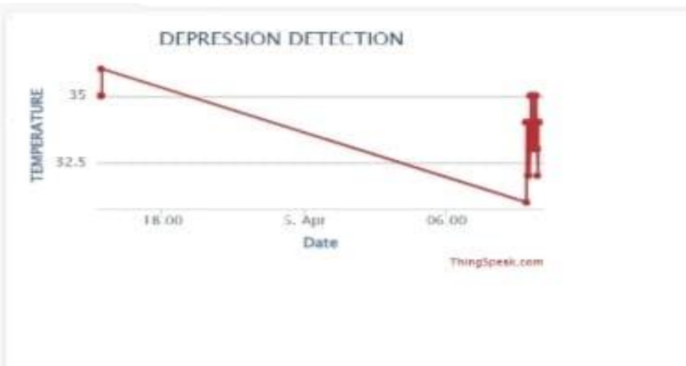

Fig. 3: Depression detection of temperature.

Thing Speak stores the received temperature data in designated channels associated with our account. we can then use Thing Speak built-in tools or integrate with external analytics platforms like Pycharm to analyze the data. The temperature sensor is connected to a microcontroller or an IoT device capable of reading data from the sensor and transmitting it over the internet. The program is then configured to send the temperature data to ThingSpeak. The graph demonstrates the relationship between temperature fluctuations and the detection of depression, highlighting how changes in body temperature may serve as a potential indicator of depressive symptoms. Studies indicate that individuals experiencing depression may exhibit alterations in thermoregulatory mechanisms, leading to variations in body temperature. Initially, as diagnostic methods for depression become more sophisticated and inclusive, there may be a gradual increase in the identification of individuals with depressive symptoms, accompanied by fluctuations in body temperature measurements. Advancements in wearable sensor technology and data analysis algorithms may further enhance the ability to monitor body temperature as a physiological marker of depression, facilitating earlier detection and intervention. Peaks and troughs in the graph may signify shifts in diagnostic strategies, technological advancements, or improvements in understanding the link between body temperature and mental health.

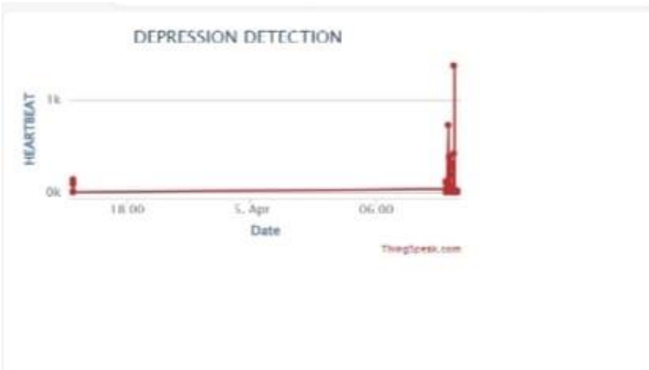

Fig. 4: Depression detection of heartbeat rate.

Connect the microcontroller or IoT device to the internet and send the heartbeat data to Thing Speak's cloud servers. The program would involve interfacing with the sensor and capturing the pulse or heart rate readings at regular intervals. The graph depicts the relationship between heartbeat patterns and depression detection, showcasing fluctuations in heart rate variability (HRV) as a potential indicator of depressive symptoms. Research suggests that individuals experiencing depression may exhibit altered HRV, characterized by less variability in the time intervals between heartbeats. Initially, as depression detection methods evolve and become more sensitive, there may be a gradual increase in the identification of individuals with depressive symptoms, paralleled by fluctuations in HRV measurements. Over time, advancements in wearable technology and data analytics may lead to more precise and real-time monitoring of HRV, enabling earlier detection and intervention for depression. Peaks and troughs in the graph may signify shifts in diagnostic accuracy, the adoption of new technologies, or changes in the understanding of the physiological markers of depression.

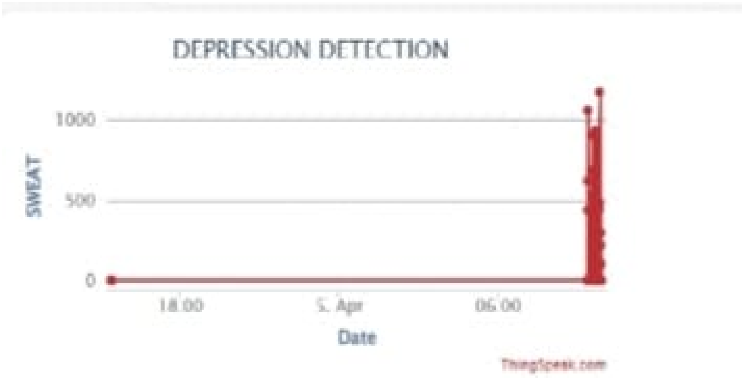

Fig. 4: Depression detection of sweat level.

The graph illustrates the correlation between sweat rate and the detection of depression, showcasing how changes in sweat production may serve as a potential indicator of depressive symptoms. Research suggests that individuals experiencing depression may exhibit alterations in autonomic nervous system activity, which can influence sweat gland activity and ultimately affect sweat rate. Initially, as methods for detecting depression become more refined and sensitive, there may be a gradual increase in the identification of individuals with depressive symptoms, accompanied by fluctuations in sweat rate measurements. Advancements in wearable sensor technology and data analysis techniques may further enhance the ability to monitor sweat rate as a physiological marker of depression, enabling earlier detection and intervention. Peaks and troughs in the graph may represent shifts in diagnostic methodologies, the development of new sensor technologies, or changes in our understanding of the relationship between sweat rate and mental health.

8. CONCLUSION

This project introduces an innovative system for sensor-based emotion recognition in faces, employing Convolutional Neural Networks (CNNs) integrated with facial analysis and various sensors including temperature, sweat, and heart rate sensors. The system is designed to accurately detect emotions, offering a deeper understanding of an individual's emotional state through robust Machine Learning (ML) algorithms. Real-time analysis of physiological data and facial expressions is made possible by a camera monitoring system, thereby enhancing decision-making accuracy in emotion recognition. The seamless operation of software and hardware components ensures efficient emotional detection, with a specific emphasis on identifying early signs of depression. Automated alerts are triggered upon detecting depressive symptoms, enabling timely interventions via platforms such as Telegram, which are accessible to caregivers and healthcare providers.

Additionally, the system incorporates advanced techniques such as feature fusion, context-aware analysis, and cloud integration for scalability, contributing to its adaptability and interpretability. Furthermore, the system employs explainable AI techniques to provide insights into its decision-making process, fostering trust and understanding among users. Continuous model evaluation, user feedback mechanisms, and integration with emerging technologies like virtual reality (VR) or augmented reality (AR) further elevate the system's capabilities, offering a holistic approach to promoting mental health and well-being. The project's comprehensive design and implementation aim to address the complex challenges of emotion recognition while ensuring user privacy, system reliability, and practical utility in real-world application.

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