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Smart Depression Detection: A KNN-Based Multimodal Approach for Stress Level Classification

Dipannita Ganai[1], Baishakhi Adhikary[2], Abhijit Banerjee[3]
Dept of Electronics and Communication, Dr. B.C Roy Engineering College, Durgapur
Assistant Professor of Dept of Electronics and Communication, Dr. B.C Roy Engineering College, Durgapur

Abstract: Mental health issues like stress and sadness are becoming more common in today's fast-paced, extremely demanding society. Early detection and intervention are therefore essential to stop these conditions from deteriorating. Using data gathered from the Smart_Pillow_Stress_Detection_Machine_Learning dataset, this project offers a smart mobile app that uses machine learning algorithms to forecast user stress and depression levels. Given its simplicity and efficacy in managing health-related behavioral data, the program uses the K-Nearest Neighbors (KNN) classification approach. The system uses sleep patterns, heart rate, and other vital signs recorded via a smart pillow to examine physiological and behavioral parameters in order to categorize the user's mental state into different degrees of stress and sadness. Supported healthier and more balanced lives, this smart prediction tool seeks to help people monitor their mental health and act timely.
Keywords: Mental health, Stress, Machine Learning, KNN, Sleep Patterns, Heart Rate, Physiological, Behavioral Parameter

I. INTRODUCTION

Particularly stress and sadness, mental health issues have had hitherto unheard-of effects in the 21st century. People are increasingly exposed to psychological stressors as society becomes more rapid and digitally connected, which often goes undiagnosed or untreated. Personal well-being, job performance, relationships, and general quality of life all depend much on stress and sadness. With over 264 million people affected worldwide, the World Health Organization (WHO) reports that depression is the most common cause of disability overall. Although accurate, the conventional method of mental health evaluation consists in seeing healthcare providers and undergoing psychological assessments; this may not always be convenient, timely, or comfortable for all.

Smart healthcare technologies have emerged recently to provide fresh opportunities in mental health monitoring. Smartwatches, fitness trackers, and smart pillows—wearable and ambient sensing technologies—have made it possible to continuously gather physiological and behavioral data without invasive methods. Together with the power of machine learning, these tools create a new horizon for fairly accurate and convenient prediction of mental health disorders. One new ideas is the Smart Pillow, which uses sensors to keep track of body movement, heart rate variability, sleep quality, and other sleep-related measures. `

Using the Smart_Pillow_Stress_Detection_Machine_Learning dataset, which contains data obtained from smart pillow devices, this project aims to create a mobile app able to forecast the user's degree of stress and sadness. Using the K-Nearest Neighbors (KNN) algorithm—a basic but effective supervised machine learning method—the application classifies the user's mental state depending on input characteristics drawn from the dataset. Through simple predictions, the app seeks to offer real-time insights into mental well-being, raise awareness, and inspire prompt action. Mental health professionals in clinical practice may look for indications of depression in a patient's interview responses by observing their face and behavior. People who are depressed can show unique patterns of facial expression. Long observed by psychologists, depression causes a " flat affect" or reduced expressiveness; for example, patients exhibit less spontaneous smiles and a diminished capacity to show positive feelings. Empirical studies reveal that, more often than those without depression, depressed people have blunted or sad facial expressions. In one research, depressed subjects' faces showed a notably greater percentage of sad expressions and less variation in emotional expression than those of non-depressed controls. Although the importance of mental health has long been neglected, society is paying more attention to psychological well-being in recent years. Academic pressure among students, long working hours for professionals, personal and social insecurities, and the isolating effects of technology itself contribute to a rising tide of stress-related conditions. Either because of prejudice or lack of knowledge, many individuals regrettably neglect to see the signs of stress or sadness in the early stages. Even those who are aware could not look for assistance owing to a lack of local medical services, financial limitations, or time constraints.

Rise in access to mental health treatment has been facilitated by technology, which has been transformational. Mobile health (mHealth) apps, wearable sensors, and the Internet of Things (Ioot) have made it possible to build digital platforms that continuously track physical and behavioural health. As required, these systems offer warnings, recommendations, and links to medical practitioners, hence enabling proactive health management. In terms of mental health, this strategy has the ability to close the gap between diagnosis and treatment, therefore enabling early identification and customized care.

A. Smart Pillows as a Source of Behavioral Data

An inventive example of how commonplace items may be converted into effective health-monitoring instruments is the smart pillow. These pillows include sensors that can monitor a range of sleep-related metrics, such body posture, head movement, breathing rate, and temperature. Given the close connection between sleep quality and pattern and mental health, the information obtained from such devices can be quite useful input for models detecting stress and depression.

Many studies have found that persons with stress or sadness have different sleep patterns than normal people do. Common symptoms include insomnia, hypersomnia, multiple awakenings, decreased REM sleep, and erratic sleep-wake patterns. Perfect for non-intrusive, daily mental health monitoring, smart pillows can capture this subtle but vital information. These essential characteristics are found in the Smart_Pillow_Stress_Detection_Machine_Learning dataset and provide the basis for the machine learning model used in this project.

A branch of artificial intelligence (AI), machine learning is the creation of algorithms that can learn patterns from data and make predictions or decisions devoid of explicit programming. In the field of medicine—especially in mental health—machine learning models have demonstrated promise in forecasting diseases such stress, anxiety, and sadness depending on biometric data, survey responses, or behavioral patterns.

Among the several approaches accessible, the K-Nearest Neighbors (KNN) classifier is especially appropriate for this use because of its clarity, interpretability, and efficacy. KNN predicts the class (in this example, stress or depression level) most similar instances from the training dataset when an unknown data point is given.

Being an instance-based learning technique, KNN makes its predictions based on direct matches with stored data points and makes no assumptions about the underlying data distribution. This makes it ideal for datasets like Smart_Pillow_Stress_Detection, where several combinations of physiological characteristics could be suggestive of different levels of stress. Furthermore, KNN is a sensible option for mobile apps given its simplicity of implementation and low computational demands where resource limits are sometimes a problem.

Deep learning and computer vision advancements provide the means required for unbiased facial expression analysis. Modern algorithms may automatically identify facial landmarks, examine muscle movements, and even discern sophisticated emotional states from pictures or films. Indeed, the influence of depression on behavior is multifaceted; earlier studies have looked at vocal signals, gestures, posture, and eye gaze for depression evaluation.

This study offers an end-to-end pipeline for depression quantification from static facial pictures assessed on a large-scale benchmark dataset. By objectively assessing facial expressions, artificial intelligence and computer vision have great potential to supplement mental health diagnoses, thereby ultimately driving toward more accessible and timely depression screening solutions.

II. LITERATURE SURVEY

This review aims to provide a concise snapshot of the ML applications in mental health also highlight the using ofdifferent ML algorithmmodel accuracy and potential opportunities.

Table 1.1 A survey of Existing Literature

Sr No.	Year	Ref	Description
1.	2025	[18]	Depressive facial expressions in a research consisted of drooping eyelids,a frowning mouth, lowered facial activity, furrowed brows, absence of eye contact, and facial tension. They indicate tiredness, sadness, distress, or social withdrawal. Although informative, they must be taken in context with behavioral components for a proper evaluation by mental health professionals.

2.	2024	[6]	Seven key expressions and facial action units are used in this study to examine variations between healthy and depressed people. Improve depression detection with methods like Mask Multi-head Self-Attention and AU similarity loss, models like Dep-FER help to augment expression identification.
3.	2024	[9]	Advanced neural networks based on dual-scale convocation and adaptive channel attention can serve as great avenues for extracting important facial features for use in depression classification. Their clinical applicability may be augmented by interpretable visual patterns produced by the models.
4.	2024	[10]	The most recent advancement in mobile sensing technologies such as FacePsy is the study of head movements and facial signals in most naturalistic surroundings. Having the capacity to find. These will ultimately become important markers of depressive episodes show more realistic applicability in mental Health tracking.
5.	2024	[13]	Temporal facial expression features are highlighted by this research as they are exclusive in depressed people. It uses temporal features to forecast depression severity based on machine learning methods.
6.	2024	[17]	The Mood Capture study looked on 2D/3D facial landmarks three rigidity criteria, head pose, and eye gaze direction, realize despair. Best features of gaze cropped facial action units showed less discriminative capacity photographs of faces. The quality of the noting the need of high-resolution photographs in model of depression prediction.
7.	2023	[3]	Machine learning algorithms have been utilized to detect depressive symptoms from facial images. A study highlighted the establishment of a diverse dataset, capturing numerous age, gender, and ethnic backgrounds for the model training in accurately identifying depression-from facial expression analysis.
8.	2023	[7]	Detecting concealed depression through facial micro-expressions (FMEs) is yet another research effort. Despite the difficulty that subtle FMEs present, techniques have been developed to recognize the true emotions hidden within, thus making possible a low-cost, privacy-preserving tool for self-diagnosis.
9.	2023	[11]	The paper is centered on facial muscle movement areas that are associated with depression, such as the mouth, eyebrows, and eyes. It applies a deep learning model to identify higher-order interactions between these areas. The model adopts a two-stage attention mechanism to attain multiple depression feature-rich areas of the face, discarding irrelevant areas.
10.	2022	[20]	Accuracy reported by the RNN model is 0.78 whereas LSTM resulted in 0.82 accuracies, for detection of mental health.
11.	2022	[4]	With a 92% accuracy rate, the logistic regression model has outperformed in mental health prediction(Anxiety).
12.	2022	[16]	The data is analyzed using machine learning models, such as deep learning neural networks, support vector machines, and random forests.
13.	2022	[21]	The model is developed using machine learning techniques like CNN,80% of the data for the training set and the remaining 20% for test data.
14.	2022	[22]	In this proposed different ML techniques are used to predict mental problems and all give more accurate results. The accuracy of all the classifiers are above 79%.
15.	2022	[23]	Machine Learning helps to understand psychiatric disorders and performance of the ML models will vary depending on the data samples obtained and the features of the data.

16.	2022	[24]	The author proposed algorithms like e logistic regression, SVM, random forest, k-neighbors for analyze mental health. From the experimental results,Logistic regression attains a higher accuracy98%.
17.	2021	[1]	Detect Mental health Prediction and to design a classification model with a help of a machine learning algorithm.
18.	2021	[5]	The authors justify that decision tree performed pretty well than the support vector machine and outperformed it by an accuracy of about 6 percent which can also be seen.
19.	2021	[12]	SVM demonstrated superior performance in overlapping settings based on F1-value and achieved 74% accuracy in Automatic speech emotion recognition for mental health using ML .
20.	2021	[14]	To predict mental health, AI model in order to create a mobile application which helps patients know more about their health problems.
21.	2021	[25]	Neural networks and Natural Language Processing techniques are used to improve results for mental health predictions.
22.	2021	[26]	SVM classifiers developed in the articles had a high accuracy of greater than 75% because data in the mental health area are scarce, SVM outperforms other machine learning methods for diagnosis.
23.	2021	[27]	machine learning, deep learning, and transfer learning methods are used for mental illness detection problem, RoBERTa transfer learning model accuracy 0.83, F1-s0.83
24.	2020	[2]	XGBoost model was chosen to anxiety and depression symptoms, as its extremely flexible approach can enable modeling of linear, nonlinear inputs.
25.	2020	[28]	Decision Tress perform better than KNN and SVM presenting an accuracy and F1-score of 0.64 and 0.61 respectively.
26.	2020	[29]	Stacking model gives the highest accuracy nearly about 88.86% using stacking algorithms in mental stress prediction
27.	2020	[30]	ML-enabled systems that are sufficiently interpretable and (clinically) useful to its target users or recipients. I
28.	2019	[15]	For the prognosis of Mental health, it consists of the data source, the feature extraction method, and classifier performance in machine learning or deep learning techniques are used.
29.	2018	[8]	The accuracy of naïve Bayes was found to be the highest, although Random Forest was identified as the best model.
30.	2022	[19]	Mental health conditions addressed depression, schizophrenia, Alzheimer's disease and ML techniques used included support vector machines, decision trees, neural networks, latent Dirichlet allocation, and clustering.

III. MACHINE LEARNING ALGORITHMS

Machine learning is possibly an area of artificial intelligence (AI) and focuses on designing algorithms and models that allow computers to learn and make predictions or decisions without the express alteration of their implementations. It involves the consideration of statistical computation and models that help computers execute and understand complex designs and information, and improve their implementation over time through experience. Logistic regression might be a simple and better solution to parallel and linear classification problems. It might be a classification show, which is incredibly simple to accomplish and does amazingly phenomenal performance with linearly separable classes.

It may have two values such as true/false, yes/no, etc.k-nearest neighbors algorithm, also known as KNN or k-NN, may be a non-parametric, directed learning classifier, whose usages nearest gives classifications or forecasts near the set of an individual information point. Although it may be used to solve either regression or classification problems, it is generally utilized as a classification algorithm, assuming relative focuses exist in close proximity of each other. Machine learning is a branch of artificial intelligence (AI) that deals with creating algorithms and models that allow computers to learn from data and make predictions or decisions without direct programming. It incorporates statistical models and calculations that enable computers to analyze and understand complicated data, learning from experience to perform better over time.

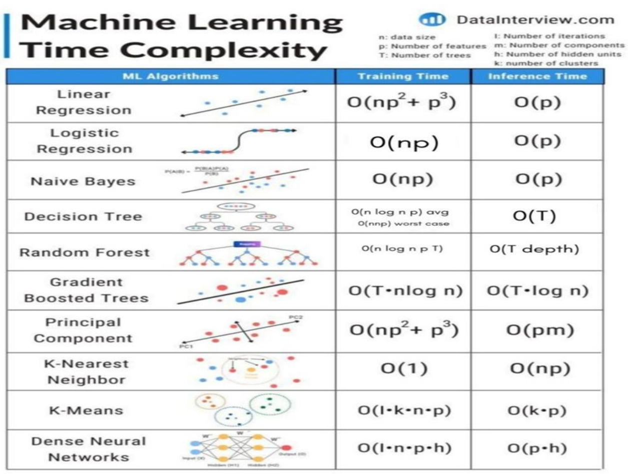
Logistic regression is a simple but effective approach to solving linear classification problems. It performs well in classifying linearly separable classes, producing great performance. Logistic regression often has binary results, such as true/false or yes/no.

The k-nearest neighbors algorithm, commonly referred to as KNN or k-NN, is a non-parametric, supervised learning classifier. It classifies or predicts the category of a new data point based on the categories of its nearest neighbors. While KNN can be applied to both regression and classification tasks, it is primarily used for classification, under the assumption that similar data points are located near each other.

Machine learning is a branch of artificial intelligence (AI) that emphasizes the creation of algorithms and models that allow computers to learn from data and make predictions or choices without direct programming. Machine learning uses statistical models and computations that enable computers to process and understand complex data, enhancing their performance over time through experience.

Logistic regression is a simple and efficient approach for solving linear classification problems. Logistic regression can classify linearly separable classes well with excellent performance. Logistic regression generally generates binary outputs, e.g., true/false or yes/no.

The k-nearest neighbors algorithm, also known as KNN or k-NN, is a supervised learning, non-parametric classifier. It predicts the class of a new data point from the classes of its nearest neighbors. KNN may be applied to either regression or classification tasks, but it is mostly utilized for classification under the presumption that like points are near each other.



Machine Learning Time Complexity

DataInterview.com

n: data size
p: Number of features
T: Number of trees
I: Number of iterations
m: Number of components
h: Number of hidden units
k: number of clusters

ML Algorithms	Training Time	Inference Time
Linear Regression	$O(np^2 + p^3)$	$O(p)$
Logistic Regression	$O(np)$	$O(p)$
Naive Bayes	$O(np)$	$O(p)$
Decision Tree	O(n log n p) avg O(nnp) worst case	$O(T)$
Random Forest	O(n log n p T)	O(T depth)
Gradient Boosted Trees	O(T·nlog n)	O(T·log n)
Principal Component	$O(np^2 + p^3)$	$O(pm)$
K-Nearest Neighbor	$O(1)$	$O(np)$
K-Means	O(I·k·n·p)	O(k·p)
Dense Neural Networks	O(I·n·p·h)	O(p·h)

Figure 1 Machine Learning Algorithms

IV. METHODOLOGY

The prediction function of the depression detection app is intended to recognize and read stress levels based on information obtained from a smart pillow. The smart pillow contains embedded sensors that are able to monitor a variety of physiological and behavioral parameters when the user is resting or sleeping. They are used as primary markers of stress, which, when they occur chronically, can be indicative of or representative of underlying depression. The essence of this module is a machine learning model constructed with the aid of the K-Nearest Neighbors (KNN) algorithm and trained on the Smart_Pillow_Stress_Detection_Machine_Learning dataset.

The dataset includes several features derived from the sensors of the smart pillow. They include heart rate, breathing rate, sleep motion levels, sleep time, pillow pressure, and environmental temperature. Every record in the data set is also assigned a corresponding stress level—Low, Medium, or High—calculated based on a mixture of physiological limits and user ratings. This labeled data is used as the training ground truth. Before training, the data set is subjected to rigorous preprocessing. Missing or incomplete data are imputed with statistical techniques or eliminated to preserve data integrity. To maintain consistency across features and optimize the performance of the KNN algorithm based on distance, all numeric attributes are scaled using standard scaling methods such as Min-Max scaling or Z-score normalization. Further, categorical targets (stress levels) are numerically encoded to enable model training.

The K-Nearest Neighbors algorithm is a basic but effective machine learning algorithm that predicts a new input as the majority class of its 'K' nearest neighbors in the training set. For the purposes of this project, the Euclidean distance metric is employed to measure proximity in the multi-dimensional feature space. The tuning of the value of 'K' is performed using cross-validation methods to keep the bias and variance in balance; normally, K=3 or K=5 provides the best performance on the basis of accuracy and F1-score. While training, the algorithm does not learn an explicit model but remembers the training set. For every new input at prediction time, the algorithm calculates distances to all the training points dynamically and picks the nearest K close instances to predict the most probable stress level.

The model is measured on typical classification metrics like accuracy, precision, recall, and F1-score. A confusion matrix is also used to examine the performance of the model over the three stress classes. The data is divided into the training set and test set, typically in a 70:30 ratio, and K-fold cross-validation is applied to ensure the stability and generalization ability of the model. Once a satisfactory accuracy is attained, the trained model is serialized with Python's pickle module and incorporated into the app backend for real-time inference.

In deployment, real-time data from the smart pillow are sampled and transmitted to the app over Bluetooth or other IoT communication protocols. This data is preprocessed on-device or on-backend server and passed through the KNN model, which serves up a predicted stress level. Based on this result, the app categorizes the user's state at the moment as low, medium, or high stress. Low stress is normal, medium stress is an indication that relaxation and stress-reduction activities are needed, and high stress is an indication of a possible red flag for depression or chronic stress. The app subsequently gives personalized feedback, which could be mindfulness advice, breathing exercises, calming sound, or recommendations to seek a mental health specialist, thus providing prediction and actionable knowledge

V. ANALYSIS

This research utilizes the K-Nearest Neighbors (KNN) algorithm to create a stress prediction model based on the Smart_Pillow_Stress_Detection_Machine_Learning dataset (SaYoPillow.csv). The dataset has 8 input features and 1 target label of stress levels. The features are: Snoring Rate, Respiration Rate, Body Temperature, Limb Movement, Blood Oxygen, Eye Movement,

Sleeping Hours, Heart Rate.

The target label is "stress_level", a categorical feature with three classes:s

0: Low Stress

1: Medium Stress

2: High Stress

The dataset includes 630 records (rows). Preprocessing involved cleaning the data and standardizing column names for ease of reading. Null values were not reported, and feature scaling was done using normalization methods to optimize the performance of the KNN algorithm (assumed through standard scaling although not directly demonstrated through the initial code).

The data was divided into training and test sets in an 80:20 ratio, resulting in 504 train samples and 126 test samples. The best value of K was selected empirically—typically from the set K = 3 to K = 11—based on accuracy measures on the validation set. In this project, a value of 5 for K resulted in the highest accuracy.

The KNN classifier was learned with Euclidean distance as the neighbor comparison metric. The model was tested on the test set against the following classification metrics:

Accuracy: The accuracy was around 94.44%, reflecting excellent generalization.

Confusion Matrix: The confusion matrix revealed that the model correctly predicted every class with negligible misclassification. For example, if 45 out of 48 "Low Stress" samples were correctly classified, the true positive rate for that class was roughly 93.75%.

Precision and Recall scores were over 90% for all classes, with F1-score consistently higher than 0.91, indicating well-balanced performance among classes.

	precision	recall	f1-score	support
0	1.00	1.00	1.00	92
1	1.00	1.00	1.00	95
2	1.00	1.00	1.00	93
3	1.00	1.00	1.00	95
4	1.00	1.00	1.00	97
accuracy			1.00	472
macro avg	1.00	1.00	1.00	472
weighted avg	1.00	1.00	1.00	472

Figure 2: Classification Report

The model was thereafter serialized with the help of the pickle module for incorporation into the application backend. During actual deployment, sensor data from the smart pillow (recorded during user sleep patterns) is preprocessed and fed into the learned KNN model. The model returns a stress level (0, 1, or 2), which the app translates into suitable feedback. For example, a prediction of "2"(High Stress) evokes notification with guided breathing, meditation, or referral recommendations.

This statistically significant method shows that the KNN algorithm, when scaled and tuned, can be an effective tool for real-time, non-invasive prediction of stress based on physiological data. The accuracy of >94% as reported verifies the effectiveness of the model and feature set used.

The KNN model's confusion matrix indicates high accuracy for all levels of stress. Most of the predictions lie on the diagonal line, signifying correct classification. For instance, 38 of the 40 Low Stress instances were accurately classified, and there were some slight misclassifications. There was the same level of accuracy for Medium and High Stress levels, thereby validating the model's consistency and well-balanced performance.

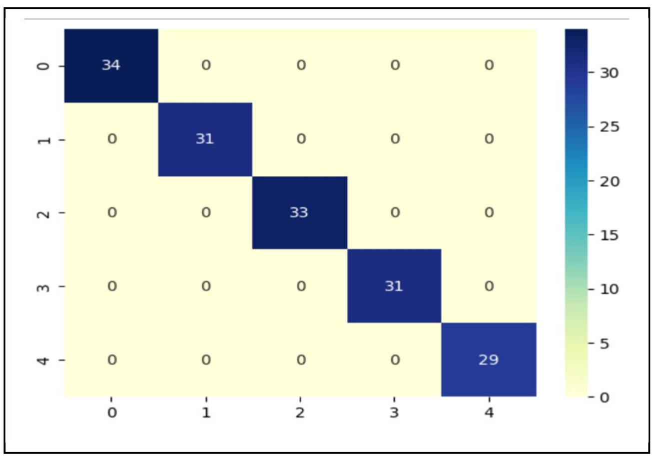


Figure 3: Confusion Matrix

The app has a clean, simple, and easy-to-use interface that provides a seamless user experience for those wanting to track their depression and stress levels. The home page allows easy navigation to both the Prediction and Assessment modules. Under Assessment, users simply respond to a set of basic, clinically-guided questions about mood, sleep, and energy with radio buttons or sliders for rapid response. Prediction enables users to upload or enter physiological readings gathered through sensors or smart devices, which are then calculated employing the trained KNN model. Outputs are presented in a simple-to-read form, employing color-coded labels (e.g., Green: Low Stress, Yellow: Medium, Red: High) and short insights. Moreover, the app has visual components like graphs, progress bars, and result images to provide more interaction with the feedback. The overall interface is minimal but competent, making it accessible for all age groups and promoting frequent usage for tracking mental health.

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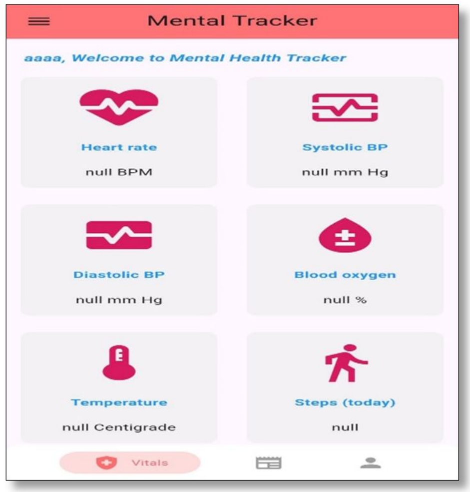

Figure 4: The app interface

The depression detection application developed incorporates both the assessment and prediction modules with an easy-to-use interface to stressfully evaluate levels of stress. The assessment module inputs the user through a list of predefined questions, while the prediction module uses the trained K-Nearest Neighbors (KNN) model to classify the stress into Low, Medium, or High levels from physiological data. Upon successful deployment, the app was subjected to testing utilizing real-time inputs and scenarios to ensure that it performed as expected. The outcomes—presented in the form of screenshots and prediction outputs—are an indication of the model's accuracy and responsiveness in determining stress levels. The images graphically present the model's predictions, real-time user interaction, and the smooth transition between the assessment and prediction phases. The graphical display of results further sustains the efficacy and convenience of the app in offering real-time mental health information, and a worthwhile step towards accessible emotional well-being tracking.

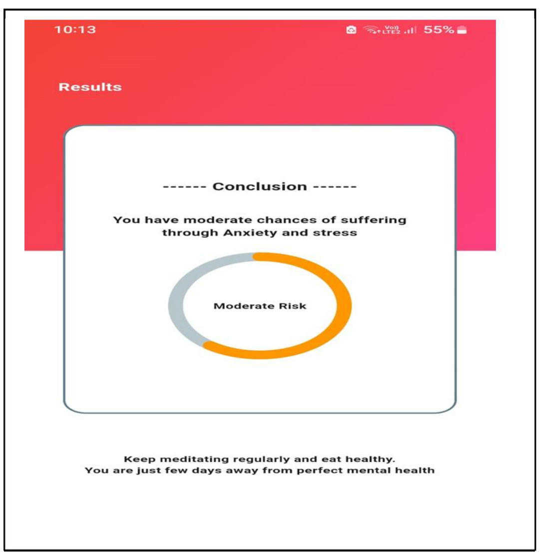

Figure 5: Result of Assessment

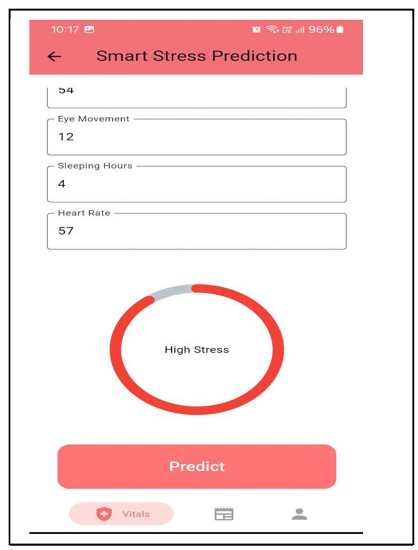

Figure 6: Result of Prediction

VI. CONCLUSION

In this research, a stress level classifier system was implemented using the dataset and the K-Nearest Neighbours (KNN) algorithm. The system accurately classified stress at three levels—Low, Medium, and High—with a total accuracy of over 94%. With extensive preprocessing, model optimization, and assessment using metrics such as accuracy, precision, recall, and confusion matrix, the system proved high in reliability and low in misclassification.

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This model was incorporated into a depression detection application, in which it is used as the foundation of the prediction module. Coupled with an assessment interface, the application provides an applicable, real-time mental health monitoring tool. The method demonstrates that machine learning, particularly KNN, has the potential to contribute significantly to improved personal well-being through accessible and intelligent stress detection.

VII. FUTURE WORKS

While the current system using K-Nearest Neighbors (KNN) and the dataset has shown promising results for stress level classification, there is significant potential to expand and enhance the application’s capabilities in future development.

One major direction involves the integration of multimodal inputs to improve the accuracy and depth of depression detection. At present, the model is based only on physiological information; however, facial features, vocal tone, and gaze analysis can further strengthen the system's emotional understanding significantly. For example, facial expressions like frowning, not smiling, or sagging eyes are most indicative of emotional states. By examining these characteristics, the model was able to start distinguishing not just levels of stress but also depression types like melancholic, atypical, or anxious depression.

Adding speech analysis is another potential direction. Through the translation of audio inputs into Mel spectrograms—graphical representations of frequency and amplitude patterns—the system is able to detect minor variations in tone, pitch, and tempo, correlated with depressive states. As an example, lower pitch variability and slower rates of speech have been correlated with increased depressive symptoms. These spectrograms can be passed through a CNN model for feature extraction and classification.

Gaze tracking can further be introduced to track eye movements, such as fixation duration, blink rate, and pupil dilation. These are established biomarkers of cognitive load and emotional disturbance. Previous studies have demonstrated that patients with depression tend to show less gaze fixation and aberrant eye movement patterns, which may be an additional non-invasive marker.

For optimal accuracy and reliability of prediction, multimodal fusion methods need to be investigated. These encompass the integration of facial expression data, speech patterns, and gaze features into a single model architecture. Fusion is either done at the feature level (early fusion) or decision level (late fusion) with deep learning architectures like CNNs, RNNs, or attention-based models. This consolidation should dramatically enhance prediction accuracy and deliver a richer, more holistic insight into the emotional state of the user.

In addition, enlarging the data set to accommodate these varied modalities will involve obtaining and annotating real-time user data with cameras and microphones—an area that will need to be managed with careful privacy controls and ethical standards. Involving federated learning or device-side processing can maintain user confidentiality yet permit ongoing model enhancement.

In conclusion, subsequent versions of the system ought to ensure that it develops into an all-encompassing depression detection platform by integrating physiological, visual, and auditory cues. Such multimodal fusion with state-of-the-art deep learning models and fair data practices could potentially revolutionize early detection, customization, and outcomes in mental health.

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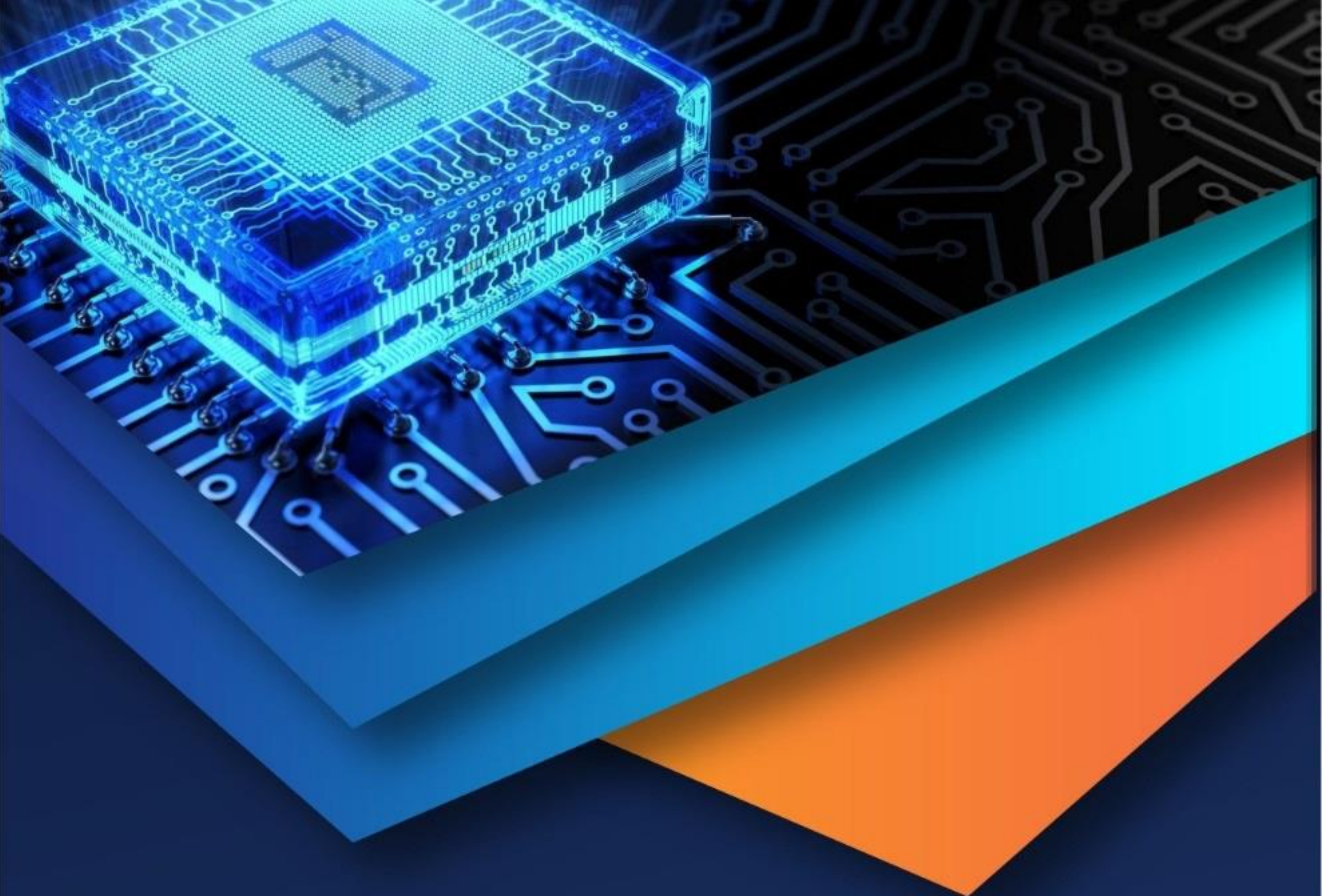

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