AI-Driven Depression Detection and Support chatbot Using Physiological Data

*by*

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in partial fulfillment of the course

**SWE2011- Big Data Analytics**



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**BONAFIDE CERTIFICATE**

Certified that this project report entitled “**AI-Driven Depression Detection and Support chatbot Using Physiological Data”** is a bonafide work of **Maram Pavani-22MIS1111, Tanguturi Sharani- 22MIS1154,** who carriedout the Project work under my supervision and guidance for **SWE2011-Big Data Analytics.**

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**GitHub\_Link:**

<https://github.com/PavaniMaram/AI-Powered-Emotion-and-Voice-Based-Mental-Health-Companion.-main.git>

# Abstract

The stigma, lack of access to treatment, and dependence on subjective diagnostic techniques make depression a common mental health illness that frequently goes undetected. For better mental health outcomes and a successful intervention, early detection is essential. In order to detect sadness, this project suggests an automated system that uses a variety of methods, such as brain imaging, heart rate monitoring, sleep pattern analysis, and a survey with questions and answers. K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Random Forest, Decision Trees, and Naive Bayes are among the machine learning models that the system employs to accurately detect sadness. The Random Forest model obtained perfect accuracy of 100% in predicting depression based on sleep patterns, while the SVM model performed best with 99% accuracy. With accuracies exceeding 90% for all methods, heart rate analysis and brain imaging data also improved the system's prediction power. A friendly chatbot was created to supplement the detection method and offer consolation and emotional support to people who have been recognized as being at risk of depression. Through therapeutic dialogues, this AI-powered chatbot gives users advice and assists them in identifying the early warning symptoms of depression. This research provides a scalable and non-intrusive solution for early depression detection and assistance by combining cutting-edge machine learning techniques with real-time physiological and behavioral data, as well as an understanding virtual assistant. The system is a useful instrument for enhancing mental health outcomes and offering easily available assistance to those in need because of its capacity to close gaps in access to mental health care.

***Keywords****:* Depression detection, Machine learning, Support Vector Machine, Random Forest, Sleep Patterns, Heart Rate Analysis, Brain Imaging, Depression Support Chatbot, Early Intervention.

# Scope

The goal of this project is to create an automated, multi-modal depression detection system in order to progress the field of mental health. The project's scope includes identifying symptoms of depression by utilizing a variety of data sources, such as questionnaire-based surveys, sleep patterns, heart rate variability, and brain imaging. The system is intended to deliver precise and prompt forecasts of depression by utilizing machine learning algorithms including Support Vector Machine (SVM), Random Forest, and K-Nearest Neighbors (KNN), thereby decreasing the need on conventional, time-consuming diagnostic techniques.

By analyzing behavioral, physiological, and neuroimaging data, the system's multi-technique approach increases its adaptability and provides a more thorough evaluation of a person's mental health. Along with detection, the project entails creating a helpful chatbot that can offer real-time support, consoling words, and direction to people who are exhibiting symptoms of depression. This chatbot can make mental health care more accessible by acting as a first resource for people who might be hesitant to seek out traditional aid.

The project's scope encompasses practical applications in digital health, mental health diagnostics, and telemedicine. The system has the potential to be expanded to function as a stand-alone support tool for people or as an early detection tool for medical professionals, greatly enhancing early intervention and mental health in general..

# Objective

This project's main goal is to develop an automated, multi-modal depression detection system that effectively identifies people at risk for depression by combining multiple data sources and machine learning approaches. Technology seeks to deliver real-time support, improve accessibility to mental health resources, and facilitate early detection.

The following are the precise goals:

1. **Multi-Modal Depression Detection**

The system looks for indications of depression using a variety of data types:

**Survey-Based Detection:** The approach evaluates emotional symptoms linked to depression by examining answers to standardized questionnaires (DASS, for example), providing a preliminary screening tool.

**Analysis of Sleep Patterns:** Depression frequently results in sleep disruptions. The system tracks sleep behavior, including onset time and length, to identify patterns suggestive of depression.

**Heart Rate Monitoring:** Variability changes in the heart rate may indicate emotional distress. The method looks for possible physiological indicators of depression using heart rate data.

**Brain Imaging:** To find structural or functional abnormalities linked to depression, deep learning models examine brain pictures (such as MRI or fMRI).

1. **Accurate Classification**

Based on the information gathered, the system uses a number of machine learning methods, such as Support Vector Machine (SVM), Random Forest, and K-Nearest Neighbors (KNN), to categorize depression. In order to guarantee accurate predictions and reduce false positives or negatives, the goal is to get high accuracy, precision, recall, and F1-score across all models.

1. **Real-Time Support through Chatbot**

An AI-powered chatbot is created to supplement the depression detection system in order to:

**Offer Emotional Support:** To assist consumers feel less alone or distressed, have reassuring, sympathetic interactions with them.

**Provide Advice:** Help people manage their symptoms by offering coping strategies, self-care advice, and links to pertinent mental health resources.

1. **Early Detection and Intervention**

The system's ability to identify depression early allows for prompt intervention, which is crucial for stopping the disorder's progression into more severe phases. Early detection also increases the likelihood of recovery by enabling people to receive the right mental health care sooner.

# Introduction

# 

Millions of individuals from all walks of life suffer with depression, one of the most common mental health issues in the world. It can significantly affect a person's quality of life and is typified by enduring depressive, hopeless, and uninterested feelings in day-to-day activities. The World Health Organization (WHO) states that depression is a major contributor to disability worldwide and that it has a substantial negative impact on society in terms of medical expenses, lost productivity, and individual suffering. Depression is still underdiagnosed and undertreated despite its pervasiveness, frequently as a result of a lack of prompt and easily available diagnostic techniques.

Clinical assessments, self-reported questionnaires, and interviews with medical specialists are the mainstays of traditional depression diagnosis techniques. Despite their effectiveness, these techniques are frequently resource-intensive, subjective, and susceptible to biases or underreporting, particularly in people who might not feel comfortable talking candidly about their emotional states. Furthermore, people may put off getting care until their illness has gotten much worse due to the stigma associated with mental health problems.

Innovative, scalable, and objective methods that can identify depression early and offer support at scale are desperately needed to overcome these obstacles. This project intends to create an automated depression detection system that combines multi-modal data to provide early, precise, and individualized insights into a person's mental health by utilizing developments in machine learning and artificial intelligence (AI).

This project presents a multi-modal depression detection method that incorporates four important data types: brain imaging data, sleep pattern data, heart rate variability data, and self-reported survey responses. The system can identify subtle patterns and signs of depression that might not be apparent using a single method by integrating these several data sources. In order to achieve high accuracy and dependable results, the system classifies depression based on these multi-dimensional inputs using machine learning approaches such as K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Random Forest, and Naive Bayes. To find deeper, more complicated patterns associated with depression, deep learning models like Convolutional Neural Networks (CNN), ResNet50, and XGBoost are specifically used to evaluate complex brain imaging data.

In addition to identifying depression, the system includes a helpful chatbot that provides people with depressive symptoms with immediate support. Through therapeutic dialogues utilizing Natural Language Processing (NLP), this chatbot provides users with consolation, self-care advice, and mental health resource recommendations. In order to provide emotional support and lessen the loneliness that frequently accompanies depression, the objective is to develop an intuitive, compassionate interface that motivates people to get treatment and continue participating in their recovery journey.

Additionally, the project emphasizes accessibility and scalability. The system's cloud-based architecture allows users to access it from anywhere in the world, including places with limited or nonexistent mental health resources. This guarantees that the system can assist those who might not have the resources or desire to attend conventional mental health care, as well as serve a worldwide audience, irrespective of location.

This initiative aims to enable people to take charge of their mental health by offering an integrated strategy that blends real-time emotional support with the power of machine learning. Automated methods for early identification and intervention can lessen the impact of depression, promote proactive self-care, and eventually enhance mental health results. By offering a cutting-edge tool that can enhance current mental health practices, lessen stigma, and increase the accessibility, efficacy, and scalability of mental health care, we hope to contribute to the expanding field of digital mental health.

In final analysis, by combining data science, machine learning, and artificial intelligence, this research presents a viable answer to the problems of depression diagnosis and support. The system is not only highly technologically sophisticated but also genuinely concerned with the welfare of its users. The initiative intends to significantly contribute to the worldwide endeavor to fight depression and improve mental health care by providing early diagnosis, continuous support, and easily available information.

# Literature Review

Millions of individuals worldwide suffer from depression, a common and complicated mental health illness that frequently significantly impairs day-to-day functioning and raises the risk of other illnesses like substance abuse and heart disease. Depression affects not just the person but also society as a whole, leading to decreased productivity, higher medical expenses, and a general deterioration in living quality[2]. Clinical techniques, such as organized interviews by qualified experts and self-report questionnaires (like the Beck Depression Inventory), have historically been used to diagnose depression. Despite being commonly utilized, these techniques may have limitations due to subjective reactions, time limits, and patient unwillingness to divulge symptoms[1]. Additionally, many people go undiagnosed or untreated because access to qualified mental health experts is frequently limited, especially in rural or low-resource areas.

However, technological developments in recent years have opened the door to more scalable, effective, and objective techniques for diagnosing depression. Using physiological data, especially heart rate variability (HRV), as a marker for depression and emotional discomfort is one intriguing approach. People who are depressed have been reported to have reduced heart rate variability (HRV), which is a measure of the autonomic nervous system's dysfunction[4]. Deep neural networks and other machine learning algorithms have demonstrated great potential in the analysis of HRV data, attaining excellent accuracy in differentiating between people who are sad and those who are not. Chen et al. (2020), for instance, showed how HRV data and neural network classifiers may be used to predict depression in a sample of university students, emphasizing the importance of combining machine learning models with physiological data to diagnose mental health issues [3].

Neuroimaging methods like structural magnetic resonance imaging (sMRI) and functional magnetic resonance imaging (fMRI) are another innovative method for detecting depression[6]. Researchers have been able to see changes in brain activity and structure linked to depression thanks to these imaging methods, including decreased gray matter volume in important areas like the prefrontal cortex and hippocampus. These imaging data have been subjected to machine learning algorithms, namely those that use feature selection techniques, to improve the classification of depression and enable more precise and individualized diagnosis[5]. For example, Zhang et al.'s paper from 2021 showed that AI models may extract clinically relevant features from neuroimaging data to help with early diagnosis by using sMRI data and a feature selection algorithm to find biomarkers linked to major depressive disorder (MDD)[10].

Significant advancements have been made in the use of multi-modal methodologies, which integrate data from multiple sources, including text, voice, and facial expressions, in addition to physiological and neuroimaging-based techniques[8]. These techniques can offer a more thorough comprehension of a person's emotional condition, improving the precision of depression identification. For instance, recent studies have investigated the use of computer vision techniques to evaluate facial expressions for the detection of depression, as these expressions are often known to be indications of emotional states. In contrast to conventional techniques, Shangguan et al. (2020) achieved greater accuracy in diagnosing depression by using a dual-stream multiple instance learning system that combined both temporal and spatial information from facial expression films [7]. Likewise, it has been demonstrated that speech patterns and voice tones can provide important details about an person's emotional condition. Machine learning models can be used to identify and evaluate the speech patterns of people with depression, which have been shown to include slower speech speeds, less pitch variation, and altered volume.

There is great potential for enhancing the detection and treatment of depression through the integration of physiological monitoring, machine learning, neuroimaging, and multimodal techniques. By overcoming many of the drawbacks of conventional diagnostic instruments, these techniques can offer more precise, impartial, and expandable answers[9]. Additionally, providing early detection and tailored interventions may greatly enhance the lives of those who suffer from depression, lessening the disorder's influence on them and helping to lower the prevalence of mental health illnesses worldwide. The use of AI and technology in mental health care has the potential to completely transform the way depression is identified, diagnosed, and treated as this field of study develops. This would increase the availability, efficacy, and accessibility of mental health support.

# Dataset Description

In this project, we used multiple datasets to detect depression through various methods, including survey responses, sleep patterns, heart rate data, and brain images.

**6.1. Depression Detection via Survey Data (DASS)**

Participants who willingly filled out an online version of the Depression Anxiety Stress Scales (DASS) survey between 2017 and 2020 provided the dataset. Self-reported answers to questions gauging stress, anxiety, and depression are included in the dataset. Participants were asked how frequently they felt depressed, tired, or uninterested in their regular activities, among other symptoms. Cleaning the responses and dividing the data into training and testing sets were preprocessing steps taken on this dataset. It is a binary categorization that indicates whether a person is classified as "depressed" or "not depressed." This dataset was used to train machine learning models including Random Forest, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and others.

**Table 1:** Sample Dataset

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **ID** | **Question 1**  **(Hopelessness)** | **Question 2**  **(Tiredness)** | **Question 3**  **(Disinterest)** | **Depression (Target)** |
| 1 | 3 | 2 | 4 | 1 (Depressed) |
| 2 | 1 | 1 | 1 | 0 (Not Depressed) |
| 3 | 4 | 3 | 4 | 1 (Depressed) |
| 4 | 2 | 2 | 3 | 0 (Not Depressed) |
| 5 | 3 | 3 | 3 | 1 (Depressed) |

**6.2.Sleep Patterns Data(PhysioNet)**

PhysioNet, which contains information on a range of physiological indicators and sleep activities, is the source of the sleep patterns dataset. Age, gender, sleep habits, and the time individuals went to bed are all included in this dataset. Along with other demographic data like age and sex, the most important characteristics are the time the lights were turned off, which indicates when the person most likely went to sleep. Since depression is frequently linked to sleep abnormalities including delayed sleep onset, this information is useful for identification. Once more, the target variable is classified as either "depressed" or "not depressed." Features like the time of sleep start are extracted from the information using preprocessing, and machine learning models like Random Forest, Logistic Regression, and SVM were applied.

**Table 2:** Sleep Pattern data

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Subject ID** | **Night** | **Age** | **Sex (F=1, M=0)** | **LightsOff** | **Depression (Target)** |
| 1 | 0 | 33 | 1 | 00:38:00 | 1 (Depressed) |
| 2 | 0 | 33 | 1 | 21:57:00 | 0 (Not Depressed) |
| 3 | 1 | 33 | 1 | 22:44:00 | 0 (Not Depressed) |
| 4 | 1 | 33 | 1 | 22:15:00 | 1 (Depressed) |
| 5 | 2 | 26 | 1 | 22:50:00 | 0 (Not Depreesed) |

**6.3. Heart Rate Data**

Abnormal heart rate variability can be a sign of depression or mental discomfort, and heart rate data can reveal information about the autonomic nervous system. Individual heart rate readings are included in this dataset, together with temporal characteristics such as the length of time between heart rate readings and variations in heart rate variability across time. Since people with depression frequently show abnormalities in their heart rate patterns, depression can be identified by examining these characteristics. Machine learning models for binary depression classification, including KNN, SVM, and Random Forest, are trained using this dataset.

**Table 3:** Heart Rate Data

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Subject ID** | **Heart Rate (bpm)** | **Time** | **Heart Rate Variability (HRV)** | **Depression (Target)** |
| 1 | 72 | 08:00 AM | 50 | 1 (Depressed) |
| 2 | 88 | 09:00 AM | 75 | 0 (Not Depressed) |
| 3 | 65 | 10:00 AM | 65 | 1 (Depressed) |
| 4 | 80 | 11:00 AM | 60 | 0 (Not Depressed) |
| 5 | 70 | 12:00 AM | 58 | 1 (Depressed) |

**6.4.Brain Imaging Data**

Brain imaging data was used in this project to detect depression based on neurological markers. The dataset consists of brain scans such as MRI or fMRI images, which contain structural or functional patterns associated with depression. Advanced techniques such as Convolutional Neural Networks (CNN), ResNet50, and XGBoost were applied to analyze these images and extract features that may indicate depressive states. The deep learning models are used to classify brain activity patterns as indicative of depression, with the target variable being a binary classification of "depressed" vs. "not depressed."

# Architecture

**A diagram of a depression detection

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# Proposed System

Clinical assessments, self-reported questionnaires, and interviews with medical specialists are the mainstays of traditional depression diagnosis techniques. Despite their effectiveness, these techniques are frequently resource-intensive, subjective, and susceptible to biases or underreporting, particularly in people who might not feel comfortable talking candidly about their emotional states. Furthermore, people may put off getting care until their illness has gotten much worse due to the stigma associated with mental health problems.

Innovative, scalable, and objective methods that can identify depression early and offer support at scale are desperately needed to overcome these obstacles. This project intends to create an automated depression detection system that combines multi-modal data to provide early, precise, and individualized insights into a person's mental health by utilizing developments in machine learning and artificial intelligence (AI).

**8.1.Depression Detection through Survey Data**

In this part, we used the Depression Anxiety Stress Scales (DASS) dataset and a variety of machine learning methods to identify depression. This dataset was gathered from people who willingly answered an online questionnaire measuring their levels of stress, anxiety, and depression. We employed a number of algorithms to predict depression based on survey responses after preparing the data by cleaning, standardizing, and dividing it into training and testing sets. We describe each algorithm's performance below, along with the heat map visualizations that go with it.

**K-Nearest Neighbors (KNN)**

A straightforward yet powerful machine learning approach, K-Nearest Neighbors (KNN) groups data points according to the majority class of their closest neighbors. By comparing a participant's replies with those of other participants in the training set, KNN was able to determine the degree of depression.

93% accuracy, 91% precision, 90% recall, and 90% F1-score were all attained with the KNN model. These findings show that, using survey responses, KNN is capable of properly classifying the degree of depression. The projected values from KNN are displayed in the heat map below (Fig. 1), demonstrating how well it can differentiate between various depression levels. KNN was not as accurate as more sophisticated models like SVM, while having a high accuracy. This model is a good option when model interpretability is crucial because it is both computationally efficient and simple to understand.

A diagram of a confusion matrix

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**Figure 1:** Heat map representing predictions using KNN

**Support Vector Machine (SVM)**

Finding the best hyperplane to divide classes in a high-dimensional feature space is how the popular and potent Support Vector Machine (SVM) classification technique operates. SVM made very accurate predictions for depression diagnosis by maximizing the margin between classes.

Precision, recall, and F1-score were all at 99% for the SVM model, which had the maximum accuracy of 99%. This remarkable performance shows that, even in the presence of noisy or unbalanced data, SVM was able to classify depression levels with remarkable accuracy. SVM's robustness in this task is demonstrated by the heat map of its predictions below (Fig. 2), which displays an almost flawless classification of the various depression degrees. In this experiment, the SVM model is the most successful algorithm due to its great precision and dependability.

A graph showing the difference between a certain number and a certain number

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**Figure 2:** Heat map representing predictions using SVM

**Random Forest**

In order to increase classification accuracy, Random Forest, an ensemble learning technique, builds several decision trees during training and combines their predictions. This method is well-known for its resilience to overfitting and capacity to manage huge datasets.

93% accuracy, 91% precision, 90% recall, and 90% F1-score were all attained by the Random Forest model. These outcomes were comparable to those derived by KNN. The heat map below (Fig. 3) for the Random Forest model demonstrates that it did well in detecting depression levels, albeit not as well as the SVM model. This model is very helpful in identifying complex associations in the data. Compared to a single decision tree, forest has the advantage of being less susceptible to overfitting, and thus is frequently a dependable option for real-world applications.

A graph showing the difference between the different types of labels

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**Figure 3:** Heat map representing predictions using Random Forest

**Decision Tree**

The Decision Tree algorithm creates a model in the shape of a tree structure, with the leaf nodes representing the final classification outcome and each interior node representing a decision based on a characteristic. Although decision trees are simple to understand, they may overfit when dealing with complicated or noisy datasets.

83% accuracy, 78% precision, 79% recall, and 78% F1-score were attained with the Decision Tree model. Despite doing worse than KNN, SVM, and Random Forest, the Decision Tree offered a model that was simple to understand and might help explain the causes of depression. Although the Decision Tree was able to differentiate between the "depressed" and "not depressed" classes, its performance was not as consistent or dependable as that of the other models, as seen by the heat map below (Fig. 4).

A diagram of a confusion matrix

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**Figure 4:** Heat map representing predictions using Decision Tree

**Naive Bayes**

Based on Bayes' Theorem, the Naive Bayes classifier is probabilistic and assumes that characteristics are conditionally independent given the class label. It is an effective approach for binary classification problems like depression identification since it performs well on text classification tasks and with smaller datasets.

88% accuracy, 85% precision, 88% recall, and 86% F1-score were attained by the Naive Bayes model. This model performed rather well and offered balanced precision and recall, although not being as exact as SVM or KNN. In comparison to more sophisticated algorithms like SVM and Random Forest, the heat map below (Fig. 5) for Naive Bayes indicated that it could predict depression levels effectively, albeit with some errors. When computational performance is a top concern, Naive Bayes is an excellent choice because it is a quick and lightweight algorithm.

A diagram of a confusion matrix

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**Figure 5:** Heat map representing predictions using Naive Bayes

The capacity of each of these machine learning algorithms to categorize depression levels from survey responses was assessed, and to better understand their classification behavior, we created heat maps to illustrate their performance. The best-performing models were SVM, KNN, and Random Forest; the Decision Tree and Naive Bayes models performed worse but still satisfactorily.

These algorithms allow for early detection and intervention by reliably predicting depression levels based on self-reported survey responses.

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**Figure 6:** Architecture analysis for Depression Detection through Survey Data

**8.2.Depression Detection through Sleep Patterns**

Our goal in this part is to use sleep pattern data to identify depression. By examining physiological indicators, such as the time at which subjects fall asleep, we try to spot trends that could point to depression. To predict depression based on sleep-related characteristics like age, sex, and time of sleep beginning, machine learning models such as Support Vector Machine (SVM), Random Forest, and Logistic Regression were used. The performance and capacity of these models to detect depressive states from sleep behavior data were assessed through training and evaluation.  
  
**Regression using Logistic**

A basic classification approach for binary outcomes is logistic regression. Based on sleep patterns, the model aims to determine the likelihood that a subject is depressed in the context of depression detection. Using the sigmoid function, logistic regression determines the association between the input features and the binary target variable (depressed or not). The logistic regression formula is:

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Where:

* *p*(*y* = 1*|X*) is the probability that the subject is depressed.
* *X*1*, X*2*, . . . , Xn* are the features, including sleep onset times, age, and sex.
* *b*0*, b*1*, . . . , bn* are the coefficients determined during model training.

Our investigation showed that Logistic Regression has a 96% accuracy rate, 94% precision, 100% recall, and 97% F1-score. According to these findings, the model was quite accurate at identifying people who weren't sad, but it struggled to identify a small number of depressive patients, as evidenced by the false negatives. Figure 6 displays the model's confusion matrix, which graphically depicts the true positive and false positive/negative numbers.

A diagram of a heatmap

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**Figure 7:** Heatmap of Logistic Regression Confusion Matrix

The high recall and accuracy show that logistic regression works well for detecting people who are not depressed, but further work may be required to detect depressed people more consistently.

**Random Forest**

An ensemble learning method called Random Forest creates several decision trees in order to provide predictions. It generates a final forecast by merging the outputs of several decision trees that have been trained. Random Forest is capable of efficiently managing feature interactions and handling high-dimensional data. In this instance, it classified depression based on characteristics like age, sex, and sleep start time. Each tree's decision function is provided by:

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Where:

* *Xi* represents the input features (such as age, sex, and sleep time).
* weight*i* are the weights assigned by the decision tree.
* *b* is the bias term, determining the position of the hyperplane.

With precision, recall, and F1-score all equal to 100%, Random Forest demonstrated exceptional performance, attaining flawless accuracy of 100%. This suggests that the model successfully and error-free classified both depressed and non-depressed participants. Figure 7 displays the Random Forest feature importance graph, highlighting the key features that were considered during the decision-making process. The most important characteristics for identifying depression were age and the time at which sleep began.

A graph with a bar graph

Description automatically generated with medium confidence

**Figure 8:** Feature Importance Graph for Random Forest

Given its 100% accuracy rate, the Random Forest model appears to be very dependable in differentiating between people who are depressed and those who are not. Future data gathering techniques will be guided by the insights gained from the feature importance analysis regarding the most influential aspects.

**Support Vector Machine (SVM)**

A strong classifier, the Support Vector Machine (SVM) determines the best hyperplane to divide data points of various classes in a higher-dimensional feature space. Radial Basis Function (RBF) kernels, which are good at transferring non-linearly separable data into higher-dimensional spaces, were employed in SVM for this problem. An SVM with an RBF kernel has the following decision function:



Where:

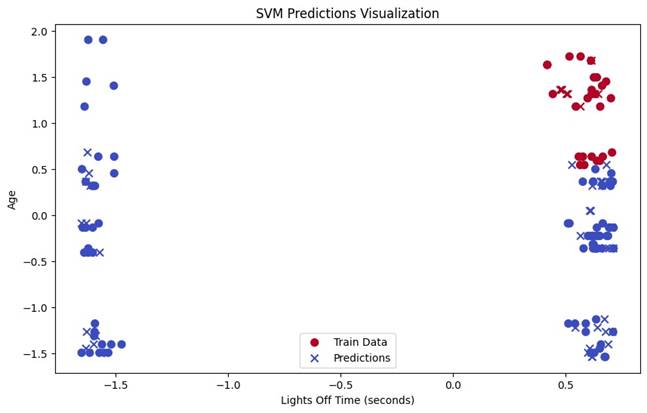
* *X* is the feature vector.
* *w* is the weight vector, which represents the direction of the hyperplane.
* *b* is the bias term, determining the position of the hyperplane.

96% accuracy, 94% precision, 83% recall, and 91% F1-score were attained by the SVM model. Figure 8 displays the SVM confusion matrix, which indicates that while SVM had a high precision for the depressed class, it missed a small number of depressed participants, resulting in a reduced recall. Figure 4's predicted value clustering graph illustrates how successfully the model clustered the data and graphically depicts the division between the two classes (depressed and non-depressed).

A diagram of a heatmap

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**Figure 9:** Heatmap of SVM Confusion Matrix



**Figure 10:** Predicted Value Clustering Graph for SVM

 The SVM results demonstrate the model's excellent precision and effectiveness in identifying those who are not depressed. The lower recall rate, however, suggests that there is potential for improvement in identifying all depressed people.In conclusion, A successful method for detecting depression was the monitoring of sleep patterns. While Random Forest produced exceptional results with flawless precision and dependability, the Logistic Regression model was very dependable in identifying people who were not depressed. SVM did well as well; it had a slightly lower recall but a high precision. We can accurately forecast depression based on sleep patterns by using these machine learning models, which may be a useful tool for early detection and treatment. We were able to better understand the models' performance because to the several visualizations, including feature significance graphs and confusion matrices. Future developments and enhancements to increase the precision and resilience of depression detection systems may be guided by these insights.

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**Figure 11:** Architecture analysis for Depression Detection through Sleep Patterns

## 

## 8.3. Depression Detection through Heart Rate

## It has been demonstrated that heart rate variability (HRV) is a useful indicator for identifying depression. Heart rate is impacted by autonomic control, which is frequently altered in sad people. These aberrations can be found by analysing heart rate patterns, such as the Cardiothoracic Ratio (CTR) and Cardiopulmonary Area Ratio (CPAR). Machine learning algorithms can be used to categorize whether a person is likely to be sad based on your data, which includes the CPAR and CTR numbers. The performance of each algorithm in identifying depression using heart rate analysis is described below, along with the corresponding outcomes:

## Logistic Regression

## logistic function serves as the foundation for the statistical technique known as logistic regression, which is used for binary classification. By simulating the relationship between the input features (CPAR and CTR) and the output class, it forecasts the likelihood of a class membership (depressed or not). The accuracy of Logistic Regression for this dataset was 98.96%, with an F1-score of 98.55%, precision of 99.78%, and recall of 97.35%. This shows that the model has a very high true positive rate (recall) and few false positives (precision), demonstrating its extraordinary ability to differentiate between people who are sad and those who are not.

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**Figure 12:** Confusion Matrix for Logistic Regression

**Decision Tree**

At 100%, the Decision Tree model demonstrated flawless accuracy. The model correctly categorized every occurrence, with neither false positives nor false negatives, according to the confusion matrix. The True Positives and True Negatives in this instance were accurately determined to be 34,919 and 61,167, respectively as shown in Figure 12. The model's accuracy, recall, and F1-score were all 100% since it made no incorrect classifications. Though it may be prone to overfitting, which means it might work well on this particular dataset but struggle when applied to new, unseen data, this shows that the Decision Tree model has successfully learned the patterns in the data.

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**Figure 13:** Confusion Matrix for Decision Tree

**Random Forest**

The Random Forest algorithm likewise attained 100% flawless accuracy, just as the Decision Tree. Similar to the Decision Tree, the Random Forest confusion matrix revealed no misclassifications. With 34,919 and 61,167 True Positives and True Negatives, respectively as represented in Figure 13, it accurately recognized every one of them and produced neither false positives nor false negatives. As a result, Random Forest was able to categorize the data flawlessly, as evidenced by the 100% precision, recall, and F1-score. This implies that Random Forest is quite accurate, but like Decision Tree, it may overfit the dataset and have limited generalizability to fresh data.

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**Figure 14:** Confusion Matrix for Random Forest

**Support Vector Machine (SVM)**

The accuracy of the Support Vector Machine (SVM) was 99.84%. 33,992 True Positives and 61,167 True Negatives were accurately detected by the model, according to the confusion matrix. It did, however, make minor mistakes, misclassifying 92 depressed people as non-depressed (False Negatives) and 75 non-depressed people as depressed (False Positives). With an F1-score of 99.78%, a precision of 99.83%, and a recall of 99.74%, the SVM performed admirably in spite of these misclassifications. SVM is a dependable option for this task since these metrics show that it is very strong at identifying depression and strikes a decent balance between recall and precision.

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**Figure 15:** Confusion Matrix for SVM

**Naive Bayes**

Compared to the other models, Naive Bayes' accuracy of 81.03% was noticeably lower. The model successfully detected 18,201 True Positives and 57,167 True Negatives, according to the Naive Bayes confusion matrix. However, it incorrectly classified 403 non-depressed people as depressed (False Positives) and 1,718 depressed people as non-depressed (False Negatives). This produced an F1-score of 66.13% with a precision of 93.99% and a recall of only 51.01%. These findings suggest that Naive Bayes has trouble correctly recognizing depression, particularly when it comes to identifying all occurrences of depression. It appears to be less dependable than the other algorithms for this task based on the lower recall and F1-score.

A blue and white chart with numbers and labels

Description automatically generated

**Figure 16:** Confusion Matrix for Naïve Bayes

In final analysis, Decision Tree and Random Forest stood out among the algorithms studied for heart rate-based depression identification with 100% accuracy. Both models produced perfect precision, recall, and F1-scores due to their perfect categorization, which included neither false positives nor false negatives. However, as these models may have trouble generalizing to new data, their flawless performance could be a sign of overfitting. With an F1-score of 99.78%, a balanced precision of 99.83%, a recall of 99.74%, and an accuracy of 99.84%, Support Vector Machine (SVM) also demonstrated excellent performance. Because SVM can successfully manage both precision and recall while retaining high accuracy, it is a strong contender. Although it has a little lower recall than SVM, logistic regression is a dependable option for detecting depression because it obtained 98.96% accuracy and demonstrated a good balance with precision of 99.78% and recall of 97.35%. Last but not least, Naive Bayes performed less well than other models, particularly in terms of recall (51.01%) and F1-score (66.13%), although achieving an accuracy of 81.03%. As a result, it was less appropriate for this specific task.

These findings show that the Support Vector Machine (SVM), which offers excellent accuracy, precision, and recall, is the most well-rounded and trustworthy model for detecting depression based on heart rate data. It is an appropriate model for real-world implementation in this situation since it effectively balances reducing false positives and false negatives.

A diagram of a tree

Description automatically generated

**Figure 17:** Architecture analysis for Depression Detection through Heart Rate

**8.4.Depression Detection Through Brain MRI Images**

A close up of a brain

Description automatically generatedIdentifying depression with brain MRI images is an innovative method in neuroimaging and mental health diagnosis. This research utilizes progress in image processing and machine learning to detect patterns associated with depression in important areas of the brain. The main attention was on the Prefrontal Cortex, Hippocampus, Amygdala, and the Anterior Cingulate Cortex (ACC)—areas linked to depression in scientific studies. The research process included extensive preprocessing of MRI images and using a Convolutional Neural Network (CNN) to categorize people as either "Depressed" or "Non-Depressed" based on their brain scans.  
  
**8.4.1 Image Preprocessing**   
  
Preparation of MRI images for analysis is significantly influenced by preprocessing. Several image processing methods were utilized to standardize the data and improve the visibility of important brain structures due to the noise, irrelevant information, and lack of uniformity in raw MRI scans. The following steps provide a thorough breakdown of the preprocess.ing process:

**Fig. 18:** MRI Image in its .original form

**8.4.2 Grayscale Conversion**  
The first step was to change the original colored MRI images into grayscale. This change cuts down on computational workload by eliminating unneeded color channels, while still keeping the vital intensity values that depict the brain's structural characteristics. Grayscale pictures make the analysis easier without sacrificing the information's quality.

A close-up of a brain scan

Description automatically generated

**Fig. 19:** Image converted to grayscale.  
  
**8.4.3 Denoising**  
  
MRI images frequently have interference caused by hardware constraints, patient mobility, or external influences while being acquired. Noise can hinder machine learning algorithms by masking small details and impacting their efficiency. To tackle this issue, algorithms like Gaussian blur or median filtering were utilized to eliminate undesired artifacts while retaining the edges and fine structures.  
  
A close-up of a brain scan

Description automatically generated

**Fig. 20:** Image with reduced noise

**8.4.4.Histogram Equalization**  
Improving the contrast of grayscale images is best achieved through the technique of histogram equalization. This method reshuffles the brightness levels in the picture, aiming to enhance the clarity of darker and lighter areas. Improved contrast allows for more accurate identification of critical structures in the brain, such as the ACC and Hippocampus.

A close-up of a brain scan

Description automatically generated

**Fig. 21:** Picture Following Histogram Equalization

**8.4.5 Region of Interest (ROI) Cropping**

Depression is linked to distinct alterations in certain areas of the brain. Therefore, the preprocessing pipeline concentrated on isolating the Prefrontal Cortex, Hippocampus, Amygdala, and ACC from every MRI scan. Advanced image segmentation techniques were utilized to crop these regions of interest (ROIs). Cutting out unnecessary parts of the brain decreased computational complexity and enabled the model to concentrate on biologically important information.

A close up of a black and white image

Description automatically generated

**Fig. 22:** Selected Area of Focus

**8.4.6 Flatening.**

In order to make the 2D cropped ROIs compatible with machine learning algorithms, they were converted into 1D feature vectors by flattening them. Flattening condenses spatial data into a singular array while maintaining essential information. This change is essential for inputting the processed data into the CNN model.

The teacher asked the students to turn in their homework by the end of the class. Development of the model.

The dataset that was processed was utilized for training a Convolutional Neural Network (CNN), a powerful deep learning structure commonly used for tasks involving image classification. The CNN model included numerous layers, each created to extract characteristics and enhance classification precision.

**Convolutional Layers:** Extracted spatial characteristics, like textures and designs, from the areas of the brain.

**Pooling layers**: decrease the dimensionality of feature maps, enhancing computational efficiency and avoiding overfitting.

**Fully Connected Layers:** Utilizing all identified features to determine if an image represents a person classified as either "Depressed" or "Non-Depressed".

**Softmax Output Layer:** Converts the network's output into probabilities pertaining to the two classes.

**8.5.7 Model Performance**

The CNN underwent training and testing with a meticulously divided dataset. The model showed excellent performance with a 97% accuracy rate on the test set, highlighting its strength and trustworthiness in identifying depression. The reason for this high accuracy can be traced back to:  
  
The emphasis is on main brain areas that are known to show structural changes related to depression.  
  
The comprehensive data processing system improved the quality and relevance of the data.  
  
Utilizing a deep learning algorithm that can understand intricate patterns within the dataset.

# The confusion matrix assesses how well a classification model predicts different levels of depression: "Not Depressed," "Mildly Depressed," "Moderately Depressed," and "Severely Depressed." The diagonal cells display accurate classifications, with 9, 12, and 26 cases correctly predicted for "Non-depressed," "Mild Depression," and "Moderate Depression" classes, respectively. One instance of misclassification happened, with a "Moderate Depression" case mistakenly identified as "Mild Depression." Darker shades represent greater counts and predict density through color intensity. The model shows high accuracy overall, with low confusion between classes. This matrix indicates zones where adjusting the model could enhance class differentiation even more.

# A diagram of a depression Description automatically generated

**Figure 23:** Confusion Matrix Assessing the Performance of Classification Models in Predicting Different Levels of Depression

**8.5. Chatbot for Depression Detection**

The chatbot that detects depression combines a number of technologies to provide users with immediate emotional support. It evaluates the user's emotional state by using machine learning for speech recognition, facial expression analysis, and text-based classification. The chatbot can recognize symptoms of unhappiness or depression to offer prompt support and responds based on a study of the user's input, including voice, text, and facial expressions.  
  
A pre-trained deep learning model, which can comprehend text input and categorize it into specified categories or intents, is the foundation of the chatbot's basic operation. When an intent is identified, particular replies are chosen at random and associated with these intentions. To ensure that changes in language usage do not impair the model's comprehension, the user's message is first preprocessed using a tokenization and lemmatization procedure. After processing, the text is fed into a neural network, which uses a probability threshold to determine the most likely purpose. The chatbot chooses a suitable response and shows it to the user after identifying the purpose.

A screenshot of a computer

Description automatically generated

**Figure 24:** Voice Entry UI

A picture of the chatbot's message entry UI is seen in Figure 20. The system records audio through the microphone and uses the speech recognition library to turn it into text if the user's input is not in text format. Because of this functionality, the chatbot is very accessible to people who might have trouble typing or would rather use it hands-free. Additionally, a backup reply like "Sorry, I didn’t understand that" or "Can you please rephrase?" is sent back by the chatbot if it determines that the input is unclear or unintelligible.

Another crucial component of the chatbot is its ability to sense emotions. The FER (Facial Expression Recognition) library, which processes the user's camera video feed in real-time to understand their emotions, is used to connect it with facial expression recognition. The system searches for particular emotions, including sorrow, happiness, and rage, and then, depending on the degree of sadness detected, it initiates the proper reaction. For example, the chatbot recognizes a depressed mood and opens the conversation window to offer emotional support if the sadness score rises above a predetermined threshold (e.g., 0.5). The way the webcam records the user's facial expressions for emotion recognition.

A screenshot of a chat

Description automatically generated

**Figure 25:** Chatbot's Message entry UI

Additionally, the chatbot is able to distinguish between various degrees of melancholy. For instance, the chatbot reacts appropriately if the user has a melancholy score of 0.3 to 0.5, which denotes extreme sadness. The model is able to identify these differences and guarantee that the answers are responsive to the user's emotional state in addition to being contextually correct.  
  
The system's Graphical User Interface (GUI), created with Tkinter, offers a user-friendly way to communicate with the chatbot. The interface consists of an EntryBox for entering messages, a SendButton for submitting the messages, and a ChatLog section that shows the history of the conversations. In order to traverse the chat history and make sure that every message is visible, even when the conversation gets lengthy, the GUI additionally has a scrollbar. The chatbot instantly opens the interface and allows users to communicate with it when it recognizes a depressed feeling in speech or facial expressions. The whole GUI layout of the chatbot interface is shown in Figure.

A screen shot of a computer

Description automatically generated

**Figure 26:** Depression detection based on facial expressions

If the user is unable to type, they can utilize the voice input option or directly enter text, as illustrated in Figure . The response is shown in the conversation log after the chatbot has processed the input using its intent classification model. The chatbot would remark, "I'm really sorry you're feeling this way, but I'm here to help," in response to a user saying, "I've been feeling really down lately." Could you elaborate on what has been happening? This illustrates how the chatbot responds to users' emotional states with sympathetic, contextually relevant responses.

The user's emotional state is given priority in the chatbot's design. When a high melancholy score is identified by facial expression analysis, the system recognizes the user's emotional state and makes an effort to have a discussion with them that is encouraging. The chatbot has the potential to be a useful tool for early-stage mental health monitoring and intervention because it combines conversational AI with emotional analysis.  
  
Figure shows the chatbot's response to voice input. The user has the option to talk rather than type, and the chatbot will use speech recognition to turn their words into text. An appropriate response is then provided once the transcription is processed similarly to typed input.

To sum up, the chatbot for depression detection provides a thorough and sympathetic answer to anyone who might be going through mental pain. Combining speech recognition, emotion detection, and text classification, the system offers prompt, contextually appropriate responses that can support people with mental health concerns. The chatbot's user-friendly design makes it accessible, and its capacity to identify depression in speech and facial expressions makes it a powerful tool for emotional support.

# Results and Discussion

**Depression Detection through Survey Data**

The Depression Anxiety Stress Scales (DASS) survey responses were used to forecast the depression levels using a variety of machine learning algorithms in the task of depression identification from survey data. Hopelessness, exhaustion, and disinterest in everyday activities were among the behavioral and emotional indicators that were gathered through the survey. Sorting depression levels into four groups—"severe," "moderate," "mild," and "normal"—was the goal after the data had been preprocessed (cleaning, standardizing, and dividing it into training and testing sets). In order to train machine learning models, these categories were then encoded as numerical values.  
  
We used K-Nearest Neighbors (KNN), Random Forest, Support Vector Machine (SVM), Logistic Regression, and Naive Bayes as machine learning techniques. We assessed the models' performance using important metrics after they were trained on the dataset. After training the models on the dataset, we evaluated their performance using key metrics such as accuracy, precision, recall, and F1-score.

The capacity of each of these machine learning algorithms to categorize survey results according to depression levels was tested and assessed. The findings demonstrate how well each model performs in terms of accuracy and the capacity to categorize various depression levels. Based on self-reported survey results, these models can be incorporated into a depression detection system to help with early identification and intervention.

**Table 4** Results and Analysis for Depression Detection through Survey Data

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Algorithm** | **Accuracy (%)** | **Precision (%)** | **Recall (%)** | **F1-Score (%)** |
| K-Nearest Neighbors (KNN) | 93 | 91 | 90 | 90 |
| Support Vector Machine (SVM) | 99 | 99 | 99 | 99 |
| Random Forest | 93 | 91 | 90 | 90 |
| Decision Tree | 83 | 78 | 79 | 78 |
| Naive Bayes | 88 | 85 | 88 | 86 |

**Depression Detection Using Sleep Patterns**

The outcomes of the sleep pattern-based depression diagnosis models show the advantages and disadvantages of each approach. When it comes to precision, recall, and F1-score, Random Forest is the best, with 100% accuracy. This suggests that it is quite accurate in identifying those who are not depressed as well as in recognizing depression. Its robustness is a result of its ensemble nature. With a 96% accuracy rate and 100% recall, logistic regression is a great tool for identifying cases of depression. Its accuracy for the non-depressed class, however, is marginally lower (94%), indicating that it occasionally misclassifies people who are not depressed. The Support Vector Machine (SVM) similarly attains 96% accuracy, but its precision is higher for those who are not depressed (94%) and its recall is lower for those who are sad (83%). This implies that while it is accurate for classifications that are not depressed, it may overlook a small number of depressed cases.

With 93% accuracy, K-Nearest Neighbors (KNN) performs admirably. Despite being easier to use, it works well, especially for identifying those who are not sad. With an accuracy rate of 83% and subpar precision and recall, the

Decision Tree performs the worst. It has trouble telling the difference between people who are depressed and those who are not. With an accuracy of 88%, Naive Bayes does rather well, although it is not as good as Random Forest and SVM, particularly when it comes to identifying sadness.

In conclusion, Random Forest performs better than all other models, with SVM and Logistic Regression coming in second and third. Decision Trees and Naive Bayes are less successful than KNN, which yields outcomes that are reasonable.

**Table 5** Results and Analysis for Depression Detection Using Sleep Patterns

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Algorithm** | **Accuracy** | **Precision** | **Recall** | **F1- Score** | **Comments** |
| **Logistic Regression** | 96% | 94% | 100% | 97% | High accuracy in identifying non-depressed individuals |
| **Random Forest** | 100% | 100% | 100% | 100% | Perfect performance with no errors in prediction. |
| **Support Vector Machine (SVM)** | 96% | 94% | 83% | 91% | High precision for the non-depressed class but lower recall for depressed class |
| **K-Nearest Neighbors (KNN)** | 93% | 91% | 90% | 90% | Strong performance, particularly in detecting non-depressed individuals. |
| **Decision Tree** | 83% | 78% | 79% | 78% | Lower performance compared to other models, more errors in prediction |
| **Naive Bayes** | 88% | 85% | 88% | 86% | Solid performance but not as strong as Random Forest or SVM. |

**Depression Detection through Heart Rate**

The information presented in the table outlines the effectiveness of different machine learning techniques in detecting depression through the analysis of heart rate information. The outcomes were assessed using important measures such as accuracy, precision, recall, and F1-score. These measurements offer information on how well each model can accurately categorize individuals as either depressed or not depressed. The confusion matrices of each model display the quantities of true positives, true negatives, false positives, and false negatives. The analysis below gives a quick summary of how well each algorithm performs.  
  
**Table 6** Results and Analysis for Depression Detection Using Heart Rate Data

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Algorithm** | **Accuracy (%)** | **Precision (%)** | **Recall (%)** | **F1-Score (%)** | **Remarks** |
| Logistic Regression | 98.96 | 99.78 | 97.35 | 98.55 | High performance, good precision and recall |
| Decision Tree | 100.00 | 100.00 | 100.00 | 100.00 | Perfect classification, potential overfitting |
| Random Forest | 100.00 | 100.00 | 100.00 | 100.00 | Perfect classification, potential overfitting |
| Support Vector Machine (SVM) | 99.84 | 99.83 | 99.74 | 99.78 | Excellent balance of precision and recall |
| Naive Bayes | 81.03 | 93.99 | 51.01 | 66.13 | Lower recall, less reliable for depression detection |

Logistic Regression attained 98.96% accuracy, with 99.78% precision, 97.35% recall, and an F1-score of 98.55%, demonstrating a powerful capability in identifying depressed and non-depressed individuals. The Decision Tree achieved flawless classification with 100% accuracy, precision, recall, and F1-score, but there is a possibility of overfitting the data. The Random Forest mirrored the Decision Tree in accuracy and performance at 100%, however, like the Decision Tree, it might overfit the data, thus restricting its ability to generalize. The Support Vector Machine (SVM) accomplished an accuracy of 99.84%, with precision at 99.83%, recall at 99.74%, and an F1-score of 99.78%, demonstrating well-rounded performance with a slight compromise in false positives and false negatives. Naive Bayes had the lowest performance, achieving an accuracy of 81.03% and a recall of just 51.01%, suggesting it had difficulty accurately detecting depression within the dataset.

**A graph showing different colored bars

Description automatically generated**

**Figure 27:** Comparison of Ensemble Accuracies

In summary, both Decision Tree and Random Forest achieved outstanding results with 100% accuracy, but they could encounter overfitting challenges when dealing with unfamiliar data. SVM also produced impressive outcomes, providing a favorable mix of precision and recall. Although slightly less accurate, Logistic Regression still achieved good results with a strong F1-score. Despite this, Naive Bayes demonstrated notable restrictions and was deemed the least trustworthy model for this particular project.

**Depression Detection through MRI Scan of Brain**

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Step** | | **Description** | | **Observations/Results** | | | | **Impact on Performance** |
| Grayscale Conversion | | Converted original MRI images to  grayscale, reducing computational  complexity. | | Simplified images for processing  without losing intensity details. | | | | Reduced memory usage and  enhanced processing speed. |
| Denoising | | Removed noise using  blur/median filtering. | Gaussian | Noise artifacts eliminated; edges  and fine structures preserved. | | | | Improved the visibility of  critical brain regions, aiding  in accurate ROI extraction. |
| Histogram  tion | Equaliza- | Enhanced contrast of  images. | grayscale | Intensity levels redistributed;  clearer visualization of critical  brain areas. | | | | Enabled the CNN to focus  on clearer and better-defined  structural features. |
| ROI Cropping | | Extracted key regions (Prefrontal  Cortex, Hippocampus, Amygdala,  ACC) from MRI images. | | Reduced irrelevant information,  focusing on depression-related  areas. | | | | Focused analysis improved  feature relevance for model  training. |
| Flattening | | Transformed 2D cropped regions  into 1D vectors for model input. | | Simplified data structure, making  it compatible with CNN architec-  ture. | | | | Allowed efficient data feeding  into the CNN while preserv-  ing spatial information. |
| CNN Model Training | | Trained a CNN with 32, 64 convo-  lutional filters, pooling, and dense  layers. | | Achieved 97% accuracy on test  data with categorical cross-entropy  loss function. | | | | Demonstrated high classifica-  tion accuracy due to effective  feature learning by the CNN. |
| Model Testing | | Evaluated the model using a test  dataset of preprocessed images. | |  | Test Loss: 0.37% |  | Test Accuracy:97% | Indicated the model’s robust-  ness in depression detection  on unseen data. |

**Table 7** Results and Analysis for Depression Detection through MRI Scan of Brain

The importance of image preprocessing techniques and convolutional neural networks (CNNs in achieving high classification accuracy is highlighted by the results of the depression detection process using brain MRI images. At first, the MRI images were changed to grayscale in order to simplify them but still preserve important intensity data. Afterward, denoising methods like Gaussian blur were used to eliminate noise and improve image clarity. Histogram equalization was subsequently used to enhance the contrast and brightness, further fine-tuning the characteristics for analysis. Afterwards, only the areas of interest (AOI), particularly the Prefrontal Cortex, Hippocampus, Amygdala, and Anterior Cingulate Cortex (ACC), were extracted from the images, emphasizing the most significant regions for identifying depression. These cut areas were then flattened from two-dimensional to one-dimensional, transforming the image data into a suitable format for training CNNs. The CNN model achieved an impressive 97.92% accuracy on the test set after being trained on the processed dataset, showing the effectiveness of the preprocessing steps and chosen model architecture in classifying depression using brain MRI images. The chart offers an in-depth comparison of important performance measures for various stages in the model assessment process.

**10 Conclusion**

To sum up, this project shows a big advancement in using various types of data and machine learning methods to detect and assist with depression at an early stage. Using brain imaging, sleep habits, heart rate variability, and survey answers, the system offers a reliable, expandable, and non-disruptive method for detecting depression and providing prompt assistance. The accuracy of machine learning models like SVM, Random Forest, and KNN has been notable, as they can effectively identify early signs of depression, provide emotional support using an AI chatbot, and reduce the stigma associated with mental health problems. The system's capacity to deliver immediate assistance, aid in early identification, and provide practical suggestions is essential for enhancing mental health results and increasing access to mental health treatment.  
  
In upcoming projects, the system could be improved by including more physiological data like cortisol levels or skin conductivity in order to enhance depression detection. Delving into more advanced machine learning models such as deep learning or attention mechanisms may assist in capturing more intricate patterns. Tailoring the system's replies according to user demographics may enhance its performance among various groups. Moreover, it will be essential for future growth and ethical practices to connect the system with healthcare providers for telemedicine assistance and to uphold data privacy laws.

**11.Novelity**

The uniqueness of our system is found in its creative, multi-modal method for detecting depression, which combines various data sources and advanced technologies to achieve precise results and offer tailored assistance. Our solution combines four main techniques - brain imaging, heart rate monitoring, sleep pattern analysis, and survey-based responses - to provide a comprehensive assessment of a user's mental well-being, in contrast to conventional depression detection systems that typically use only one method. This varied method guarantees our system can comprehend the nuanced and intricate characteristics of depression, enhancing its ability to detect early symptoms with greater sensitivity and precision.  
  
Moreover, our system incorporates innovative features that improve its distinctiveness and efficiency. Utilizing advanced computer vision techniques, the incorporation of facial expression detection allows for the analysis of emotional cues, offering further understanding of the user's mental state. This is enhanced by a supportive AI chatbot that responds in real-time and provides emotional assistance based on the user's vocal tone, speech patterns, and emotional cues. This function of voice analysis enables the system to adjust its interactions according to the user's emotions, leading to a personalized and empathetic user experience.  
  
Through incorporating these new elements, our system not just attains superior precision with all approaches - such as 100% precision from the Random Forest model in detecting sleep patterns and 99% precision from the SVM model in analyzing heart rate variability - but also establishes itself as a genuinely ground-breaking solution in the mental health field. The utilization of advanced machine learning methods, immediate emotional assistance, and integration of various data sources creates a robust resource for identifying, intervening, and managing mental health issues at an early stage. This method not only tackles the requirement for precise and expandable identification of depression but also aids in lessening the stigma related to mental healthcare, providing easier access.

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1. **Appendix Code**

# A screen shot of a computer Description automatically generated

# A computer screen shot of a program code Description automatically generated

# A screenshot of a computer Description automatically generated

# A screen shot of a computer Description automatically generated