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A Machine Learning Framework for Enhanced Depression Detection in Mental Health Care Setting

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ABSTRACT

One of the most overlooked yet vital aspects of our general well-being in the modern day is mental health. There are many persons who experience various mental health conditions and diseases. The present investigation describes an improved model for diagnosing depression in clinical and healthcare environments with the help of the DAIC-WOZ Depression Database. The data set used in this work comprises 80% training data and 20% testing data; criteria like classification evaluation, such as accuracy, precision, recall and the F-index measures, are applied here to evaluate the efficiency of the selected machine learning models, including KNN, CNN, MTL and XGBoost. Based on the archival findings, it is clear that algorithm performance of the XGBoost model is superior to other models positively categorised pictures with an accuracy of 97.02%; precision of 97.03%, recall of 97.01 % and F1-score of 97.02%. A comparison between the outcomes of Multi-Task Learning (MTL), More specifically, it will draw from Convolutional Neural Networks (CNN), and K-Nearest Neighbours (KNN). Classification models illustrate that XGBoost has a superior performance across all measurements for offering accurate depression detection in clinical practice. One more is the use of more extensive multiple modalities, e.g., physiological data or social media, to enhance the rate of depression identification. Transformers, as well as the integration of deep learning hybrid networks, may be used to capture data dependencies in the dataset.

Keywords : Mental Health, Depression, Depression Detection, Machine Learning, Diagnosis, Healthcare Technology, DAIC-WOZ Dataset.

I. INTRODUCTION

According to the World Health Organisation (WHO), mental health is defined as a state of well-being. In which individuals successfully negotiate life's obstacles, develop their skills, work, have fulfilling relationships, and actively participate in their community[1][2]. Another client needs to focus on mental health as this is important for survival and helps people handle challenges in life, build relationships, and be productive in the community[3][4]. Another client needs to focus on mental health as this is important for survival and helps people handle challenges in life, build relationships, and be productive in the community[5]. Another client needs to focus on mental health as this is important for survival and helps people handle challenges in life, build relationships, and be productive in the community[6]. Major depression is defined as having a low mood or depressed, hopeless, or empty sensations, as well as a lack of enthusiasm for everyday life that interferes with the way people think, feel and behave[7].

In mental health care, a timely diagnosis and assessment of patients for depression is crucial in handling these patients and determining their prognosis [8]. Clinical interviewing and self-report checklists have been the major measures used for diagnosing depression in the past [1]. Nevertheless, such methods can take a lot of time, are qualitative and, moreover, are based on patient's willingness for disclosure. However, in the remote or low-resource setting, diagnosing depression is difficult because there are very few health care providers[9]. Such limitations require that much more efficient and much more scalable solutions be implemented to fit mental health care settings [10].

Recent developments in the application of AI and ML technologies have made it possible to discuss new possibilities in detection of depressions which are more effective, formal, and large scale [11][12]. AI and ML can provide an overview and precise identification of forms of depression that are present in people and can be effectively treated with methods that can drastically improve their mental state[13][14]. These technologies enable automatic and real time depression detection that may help clinicians in early identification of at risk patients and early intervention [15].

Motivation and Contribution of the Study

Mental health disorders, most especially depression, have been considered a leading health crisis in the world, and there are more people who are diagnosed with these illnesses today than there were at any other time in the past. Since Early depression identification is crucial in ensuring the patient obtains appropriate treatments when ailing, typical assessment approaches are based on self-reported information, which is often ridden with error. This study is necessitated by the existing gap in literature as the purpose of enhancing the process of detection of depression by using objective data analytically driven targets. This paper contribution are listed below:

- for depression detection using multimodal data from the DAIC-WOZ Depression Database (audio, video, and text).
- Implementation of preprocessing techniques, including noise removal using the GMW method to enhance audio signal quality for better analysis.
- Application of the SMOTE method to address class imbalance and ensure improved model performance for minority class detection.
- Utilization of the BERT tokeniser for tokenising text data to prepare it for ML models, ensuring consistency in model inputs.
- Evaluation of multiple ML models, including KNN, CNN, MTL, and XGBoost, with F-metrics, recall, accuracy and precision metrics.

Structure of paper

The rest of the document is structured as follows: Section II discusses earlier studies on depression identification. Section IV presents an analysis of the findings, whereas Section III presents the methodology and processes. A summary. The conclusion of Section V includes a summary of the study's other implications and suggestions for further study.

Literature Review

This study, Wang and Liu (2022) suggests a deep model hybrid architecture-based depression detection model to help medical professionals diagnose depression. This research examined 157 Chinese participants. To determine the various emotional shifts that occur when reading various portions of spoken words, they extract the low-level audio elements. They employ a multi-map to identify sadness and a convolutional neural network to extract deep spectrum information. According to the trial findings, voice depression detection accuracy reaches 82.70%, which can help physicians diagnose depression [16].

In this research, Aggarwal, Girdhar and Alpana (2022) To explore unique the probabilistic forecasts of an imprecise kind of mental illness by developing machine learning predictive models with machine learning algorithms, a thorough literature review was conducted. In light of the ongoing pandemic, a number of previous research studies were examined, and the evaluation results indicate that Machines (Support Vector Machine), meaning that the accuracies were: 98.6% for support vector machines and 97.9% for random forest, Gradient Boosting Machine, and K-Nearest Neighbours are the algorithms that predict mental illness the best. (97.07%) [17].

This study, Raut et al. (2022) utilise user-provided textual remarks gathered through an online application to forecast users' personalities and mental health, after building and training machine learning models on the dataset, including ensemble models, the Random Forest, Naïve Bayes, Support Vector Machine, KNeighbors Classifier, and Logistic Regression; the highest accuracy score was chosen based on the accuracy prediction from k fold cross-validation. Similarly, for the personality traits of introversion, intuition, reasoning, and perceived talents to predict 16 characters archetypes across four axes; for evaluation on the same data set the XGBoost classifier assigned high specificity. When it comes to predicting personality, this classifier has the highest accuracy at 67.68 percent. On the other hand, the greatest accuracy of Logistic Regression in predicting mental wellbeing is 96.05 percent[18].

This study, Yan, Tu and Wen (2022) aims to track depressive symptoms using sequential mobile data collected from sensors on phones. Initially, in order to effectively exploit the sequential data in mobile, they created a deep-learning model called Dep-caser. They then present a discretisation technique based on Information Value to address outliers and sparse data. They enrolled 257 participants in all, and they collected Data from their iPhones and electronic bands during a five-day period. They have carried out two trials to investigate the efficacy of the discretisation and Dep-caser approaches, respectively. Dep-caser surpasses the majority. Discreteisation enhances the performance of the deep learning model, which further the findings enhances the performance of machine learning approaches and attained an overall accuracy of 0.83[19].

This study, Acharya and Dash (2022) suggests a cutting-edge deep learning-based system for the effective identification of clinical depression in prospective patients. A novel method for classifying a current Conversion of AFEW-VA dataset in terms of relative output of the sad class and the non-depressed class is given below in terms of valence and arousal value of different persons from their video frames. Additionally, the regions of interest (ROIs) for the complete face, eyes, and mouth are taken from the classified dataset and used to use transfer learning to train three different pre-trained 2DCNN models: Those include ResNet50, VGG16 and InceptionV3. This is established to prove that the accuracy of the combined models with the ResNet50 architecture is higher than the architectures of VGG16 and InceptionV3 with the overall accuracy value of 0.95[20].

This study, Pan et al. (2019) proposes an image cognition-based experimental paradigm to capture participant eye movements and reaction times, creating one of the biggest depression datasets. They employ a typical Classifier using Support Vector Machines to distinguish between normal controls and depressed patients after extracting the relevant R-T (Reaction Time) and E-M (Eye Movement) variables that may indicate the participant's attention bias. Their approach exceeds the prior comparable method with an accuracy of up to 86%. Their classification performance in their extensive dataset is exceptional[21].

Table I summarises various studies on depression detection and mental health prediction, detailing datasets, methodologies, performance metrics, and research limitations. It highlights, With the help of ML & DL, paying attention to the possibilities and perspectives of enhancing diagnostic accuracy in the future.

Table 1. Summary of the related work on Depression . Detection in Mental Health Care using machine learning methods

References	Dataset	Methodology	Performance	Limitations & Future Work
Wang and Liu, (2022)	157 Chinese subjects	Word reading experiment for rapid emotional change; low-level audio feature extraction; CNN and Multi-map for depression detection.	82.70% accuracy in speech depression recognition.	Limited to speech data; future work can focus on multimodal data integration and larger subject samples.
Aggarwal, Girdhar, and Alpana, (2022)	Literature survey, multiple studies reviewed	Machine learning algorithms evaluated: Gradient Boosting Known as Machine, SVM, Random Forest, Naïve Bayes, and K-Nearest Neighbours.	SVM (98.6%), Random Forest (97.07%) for mental illness prediction.	Relies heavily on existing literature; future research could explore new datasets, real-time predictions, and combining multiple algorithmic outputs.
Raut et al., (2022)	User comments from a web application	Data encoding utilising Count Vectorizer and Label Encoder; SVM, Random Forest, Naive Bayes, KNeighbors, XGBoost, and Logistic Regression are examples of machine learning models.	Logistic Regression: 96.05% for mental health prediction; XGBoost: 67.68% for personality prediction.	Dataset limitations in diversity; future work could collect larger, unbiased datasets and explore ensemble models for personality prediction.
Yan, Tu, and Wen, (2022)	257 participants; five-day sequential mobile data	Deep learning model (Dep-caser) utilising sequential mobile data; Information Value-based discretisation to address data sparsity and outliers.	Accuracy: 83% after implementing Dep-caser and discretisation techniques.	Limited to mobile and sensor data; future work can include other types Using information, including medical records and social media, to increase the precision of diagnosis.

Acharya and Dash, (2022)	AFEW-VA dataset	Deep learning-based detection using transfer learning; extracted ROIs (facial, eye, mouth regions) from video frames; 2D CNN models that have already been trained: Inception V3, VGG 16 and Residual Network 50.	ResNet50 achieved the best accuracy: 95%.	Focuses on visual data; future work can explore real-time video analysis and extend datasets for higher generalizability.
Pan et al., (2019)	Large-scale depression dataset on the basis of picture cognition	Eye Movement and Reaction Time (R-T) (E-M) feature extraction; SVM for classification of depressed and normal participants.	Accuracy: 86% using SVM on R-T and E-M features.	Limited feature scope; future research could investigate combining R-T and E-M features with other biomarkers and explore deep learning models for enhanced performance.

Methodology

The methodology for enhanced depression detection in a mental health care setting utilises the DAIC-WOZ Depression Database, which includes a combination of audio, video, and textual information from 59 individuals who were depressed and 130 people who weren't. Data preprocessing involves noise removal using the Gain Modulated Wavelet (GMW) technique, which enhances audio quality by eliminating background noise and normalising amplitude levels. The dataset is then balanced using the SMOTE technique to address class imbalance, generating synthetic samples for the minority class to improve model performance. Feature extraction, including Auto Cepstral Fusion, is applied to the preprocessed audio data to extract meaningful features. Additionally, text data from the database is transformed into integer values for model input by tokenising it with the BERT tokeniser. A confusion matrix using machine learning assessment standards such as accuracy, precision, recall, and f1-score is used in this study to assess the accuracy and relevance of the predictive model as KNN, CNN, MTL, and XGBoost Membership datasets are trained and tested using a 80:20 split between the training and testing protocols.

The implementation steps are depicted in Figure 1 below.

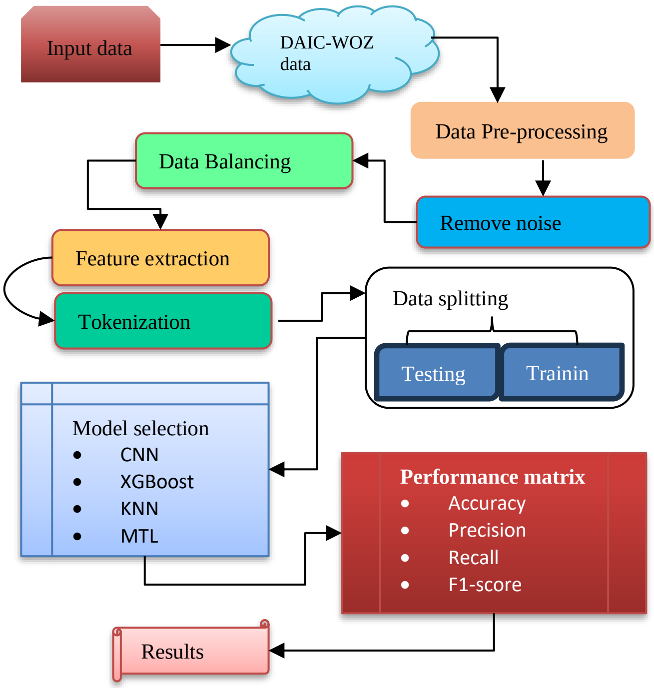

Fig. 1. Flowchart for depression detection in mental health care

The following steps of implementation are briefly explained below.

Data Collection

In mental health care, depression is detected using the DAIC-WOZ Depression Database. The dataset includes questionnaire answers and responses from 130 non-depressed and 59 depressed individuals. It also includes text, audio, and video components that illustrate patients' verbal and nonverbal signs of sadness. Figure 2 displays people who are depressed and those who are not.

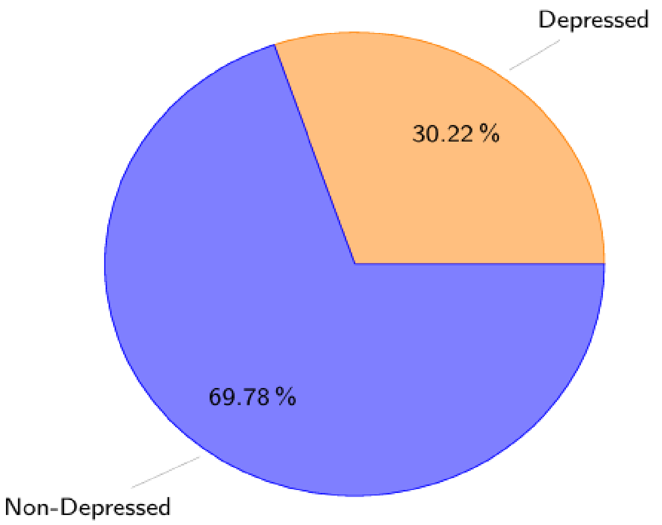

Fig. 2. Depressed and Non-Depressed Participants.

Figure 2 illustrates the distribution of People who are categorised as depressed and those who are not. Approximately 69.78% are categorised as non-depressed, while 30.22% are identified as depressed, highlighting a higher proportion of non-depressed individuals in the data.

Data Preprocessing

The act of converting largely qualitative data into structured datasets suitable for other forms of analysis is known as data preparation[22][23]. Pre-processing of audio signals typically involves several steps aimed at enhancing the signal's quality or extracting useful information from it. Further pre-processing steps are listed below:

Remove noise

Gain Modulated Wavelet (GMW) Technique removes background noise from audio recordings, capturing both low- and high-frequency information in voice signals and normalising audio signals to ensure consistent amplitude levels across recordings [24][25].

To remove noise from audio signals, the GMW technique strengthens the adaptive gain model and discrete wavelet transform methods[26].

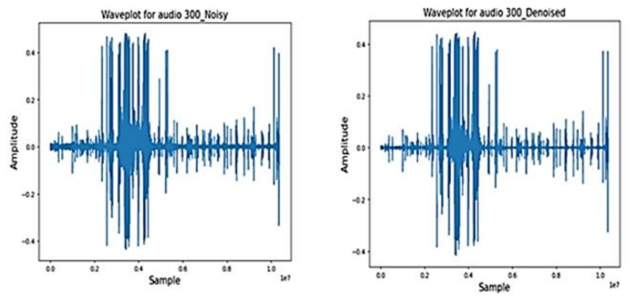

Fig. 3. Before and after noise remove

Figure 3 compares waveplots for noisy and denoised audio signals. The noisy waveform shows small amplitude fluctuations superimposed on the main signal, indicating noise interference, while the denoised waveform appears smoother, with significantly reduced noise. Noise in audio signals degrades quality, making them distorted and harder to understand, and complicates processing tasks like speech recognition and music retrieval. Removing noise enhances audio clarity and improves the performance of downstream tasks that depend on clean signals for accurate analysis and processing.

Data balancing

The dataset was balanced using the SMOTE approach, which comes after the noise removal procedure. SMOTE balances class distribution, making the model more robust and less biased towards the majority class[27][28]. Although its effectiveness depends on the dataset and problem, it is a valuable tool to enhance machine learning models' performance and handle unbalanced datasets by creating synthetic samples for the minority class. [29][30]. Figure 4 below shows the dataset modelling (before and after balancing the dataset).

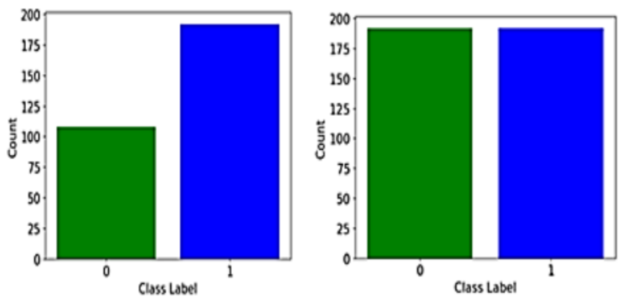

Fig. 4. Before and after data balancing

Figure 4 illustrates the impact of data imbalance and its correction. In the imbalanced dataset (a), the significantly taller blue bar for class 1 indicates a much larger number of samples compared to class 0, leading to a biased model that struggles to predict the minority class (class 0) due to insufficient representation. In contrast, the balanced dataset (b) shows nearly equal bar heights for both classes, suggesting that techniques like oversampling, undersampling, or synthetic data generation have been employed to equalise class distribution.

Feature extraction

In audio signal processing, extracting relevant features from pre-processed data is crucial for various applications[31]. However, difficulties arise with generalisation and interpretation due to the raw nature of voice signals, leading to poor performance in feature extraction [32]. A technique called Auto Cepstral Fusion feature extraction is introduced to address these challenges[33].

Tokenization

In the DAIC-WOZ dataset, using transcript data for depression detection, which is text data. However, the model does not take text directly as input; it takes integer values[34][35]. That is why they need to tokenise the text dataset. BERT tokeniser is used for tokenisation.

Data Splitting

Data, train data, and test data are the divisions of the DAIC-WOZ database. 80:20 is the splitting ratio. The remaining 20% of On the remaining 20%, the data is employed in order to evaluate the performance of the model after the training process.

Classification Models

An ensemble tree technique called the XGBoost algorithm iteratively combines weak learners. [36][37]. The method estimates and subsets a variety of trees to the pseudo residuals, actual value minus the project value, and applies boosting techniques to minimise the residual[38]. Ultimately, this reduces the possibility of overfitting and results in a classification model that works better.[39][40]. The "boosting" strategy successively combines they label weak classifiers to create a stronger classifier by using weak learner in the direction of the gradient of the loss function. Subsequent to fitting each tree, the model produces the expected values by (1):

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i) \quad (1)$$

where xi is feature vector of the ith data input and fk is a classfication tree k. The program classifies binary data using the LogLoss.[41][42]. A regularisation term regulates the model's complexity in order to eliminate overfitting and lower the model's complexity. The XGBoost algorithm's regularisation term is (2):

$$\Omega = \gamma L + \frac{1}{2}\lambda \sum_{j=1}^{L} w_j^2 \quad (2)$$

where γ and λ are the number of leave, L is the degree of regularisation, and wj 2 is the score on the jth the sigmoid transfrom can generate the probability[43][44]The composite function of the model is the result of the regularisation and the loss function(3):

$$obj^{(t)} = \sum_{i=1}^{n} L\left(y_i, \hat{y}_1^{(t-1)} + f_t(x_i)\right) + \Omega(f_t) (3)$$

where Ω is the regularisation term and L is the loss function. Gradient descent is used to maximise the model's objective function[45]. Gradient descent iteratively optimises an algorithm's parameters in an attempt to obtain the global minimum of a differentiable function[46]. According to the literature, the XGBoost algorithm is one of the youngest of the algorithms and yet it has so much potential[47][48]. The approach is computationally efficient in addition to performing well with mixed data types, as this study demonstrates.

Model Evaluation

The appraisal of a model is essential to comprehending its practical utility. It makes predictions about the model's performance on fresh data, with varying scores indicating various model components[49][50]. Talk about the categorisation problem's evaluation metrics in this section [51]. they use a 2x2 confusion matrix for binary classification. While Precision is the quantity of true positives (TP), whereas Measures of FP includes the amount of instances that are negative but were grouped under positive results. TN is the number of negative cases correctly identified; FN is the number of truly positive states which were classified erroneously as negative.

Accuracy: The ratio of accurately predicted samples to total samples is the subject of this discussion.[52]. Equation (4) stands for the accuracy formula.

$$Accuracy = \frac{TP+TN}{TP+TN+FN+FP} \quad (4)$$

Recall: It means the proportion of "positive" samples that are classified as such, that is the true positive rate. Equation (5) stands for the method of finding test collection retrieval rate.

$$Recall \ = \frac{TP}{TP+FN} \quad (5)$$

Precision: In percentage, in proportions that relate to the proportion of samples assumed to be "positive," which is indeed "positive". Equation (6) presents the symbol of the formula for precision.

$$Precision = \frac{TP}{TP+FP} \quad (6)$$

F1-Score: As put by Martin, F1-score is the average of Precision as well as Recall with the equation F_{1} =2.Pr*Re/(Pr+Re). Equation (7) stands for the computational method of F1-score.

$$F1 - Score = \frac{2 \times precision \times recall}{precision \times recall} \quad (7)$$

These evaluation matrices are used in the identification of depression in the mental health sector.

Result Analysis And Discussion

The proposed outcome for depression detection in mental health care contexts was tested used the DAIC-WOZ dataset in this part to determine which machine learning models produced the greatest f1-score, accuracy, precision, and recall. The performance of the XGBoost model is shown in Table II below, and the graph is also shown. This model when compared with the prevalent models such as KNN[53], CNN[54], and MTL[55] those that give performance in Table III on the same data set and evaluation criterion.

TABLE I. RESULTS OF THE XGBOOST MODEL FOR DEPRESSION DETECTION ON ON DAIC-WOZ DATASET

Performance matrix	Extreme Gradient Boosting, (XGBoost)
Accuracy	97.02
Precision	97.03
Recall	97.01
F1-score	97.02

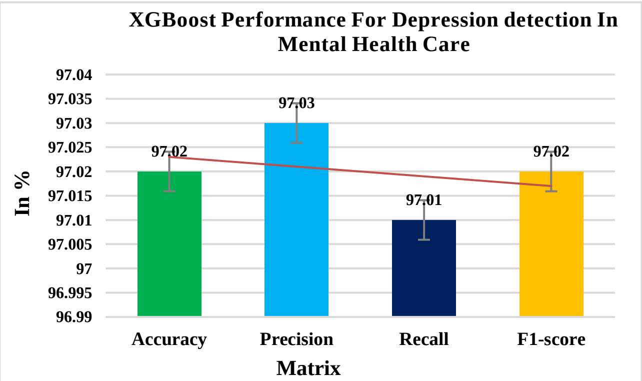

Fig. 5. Bar Graph for XGBoost Model Performance

The XGboost is model performance as depicted in Figure 5. The evaluation of the performance of the constructed XGBoost model shows that the proposed model achieves an accuracy of 97.02%, precision of 97.03%, recall of 97.01% and F1 score of 97.02%. These metrics show the remarkable specificity and sensitivity of the model and are a promise of equally high reliability of its work in terms of all selected criteria.

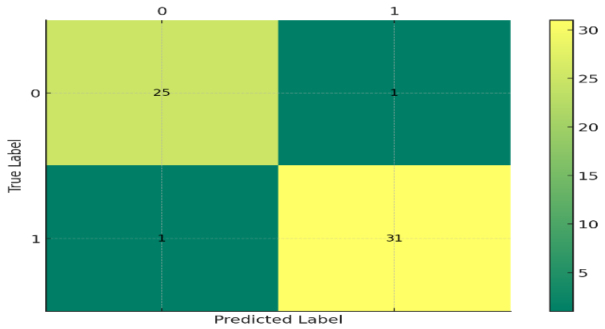

Fig. 6. Confusion Matrix for XGBoost Model

Figure 6 confusion matrix analysis for Strong performance is revealed by the XGBoost model with an accuracy of approximately 96.55% (56 correct predictions out of 58). The model correctly classified 31 positive instances (TP) and 25 negative instances (TN), with only 1 FP and 1 FN. This indicates high specificity in identifying negative cases and strong sensitivity in detecting positive cases, though there is minor room for improvement in reducing the False Negative rate to further enhance the model's overall performance.

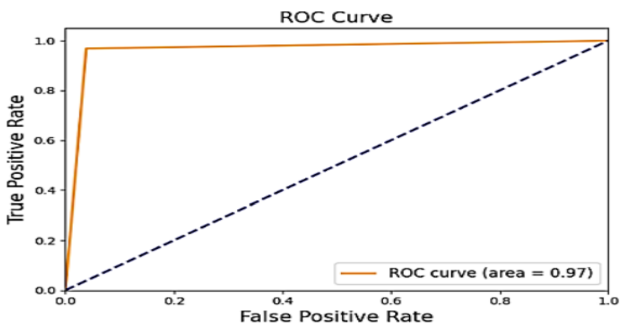

Fig. 7. ROC Curve for XGBoost Model

Figure 7 To illustrate how effectively a classification model works, a ROC curve plots the TPR (True Positive Rate or sensitivity) against the FPR (False Positive rate or 1-specificity) for different thresholds. Better performance is indicated in the top-left corner, and the classifier's overall ability to categorise these two classes is measured by its AUC. Additionally, the ROC curve that results shows flawless classification performance, reaching an AUC of 0.97. The circumstance when an analyst selects patterns to invest in at random is depicted by the diagonal line, and the model's performance in the classification function is demonstrated by the curve's position above this line.

TABLE II. COMPARATIVE ANALYSIS FOR DEPRESSION DETECTION ON DAIC-WOZ DATASET

Models	Accuracy	Precision	Recall	F1-score
KNN	72.73	79	88	83
CNN	68	67	71	69
MTL	74.5	70.1	71.5	74.6
XGBoost	97.02	97.03	97.01	97.02

In Table III different models for depression detecting in DAIC-WOZ dataset have been compared. Overall performance detailed results show that the XGBoost model surpasses all the others with outstanding values were 97.02%, 97.03%, 97.01%, and 97.02% for accuracy of precision and recall, F1 score respectively. In contrast, the Multi-Task Learning (MTL) model achieves 74.5% accuracy, 70.1% precision, 71.5% recall, and 74.6% F1 score. With better precision (79) and recall (88), the accuracy of KNN is 72.73%, resulting in an F1 score of 83. This issue yields lower results with the Convolutional Neural Network (CNN) model, specifically, is: accuracy = 68 %; precision = 67; recall = 71; F1-score = 69. These findings show that the XGBoost algorithm is a superior choice for tasks involving the diagnosis of depression.

Conclusion And Future Scope

In this case the human condition that is affected is depression which is a mental disorder. It is also the leading of overall global burden of disease and it also contributes to disability. To assist depressed patients in healthcare departments, it is very important to detect depression from text automatically. Here, they introduced an advanced scheme of using the DAIC-WOZ Depression Database for depression detection. Through cleaning the noise from the dataset, balancing between overlapping data through SMOTE and AutoCepstral Fusion from the feature data improved the quality of the data. Performance comparison of the XGBoost model has been made with four other algorithms, such as KNN, CNN, and MTL, and all results show that the proposed method is better than others with precision 97.03%, recall 97.01%, accuracy 97.02%, and F1-score 97.02%. These findings are crucial to support the previous, * and assert that XGBoost is an effective machine learning algorithm to classify participants as being or not being depressed in a mental health care environment. The comparative analysis also highlighted that XGBoost outperforms other studied models concerning main evaluation metrics. This paper offers potential for depressed detection and the subsequent research can specialise in improving its efficacy and examining its applicability for the clinical practice for complementing real-time depression determination.

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