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Depressive Disorder Diagnostic Assessment Framework: A Review

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***Abstract*— Major Depressive Disorder (MDD) is one of the psychiatric condition that is undetected due to the limitations of subjective diagnostic methods. This study proposes a deep learning approach that combines the Convolutional Neural Net- works (CNNs) with a Multi-Layer Perceptron (MLP) to increase the diagnostic accuracy. The system is trained on the datasets containing demographic, psychological, and clinical attributes obtained from the NHANES depression dataset. The process includes the data preprocessing, feature selection, dimensionality reduction, and classification. Evaluation results shows that the MLP outperforms traditional machine learning models, such as Support Vector Machines, Logistic Regression, K-Nearest Neighbors, and XGBoost, achieving an accuracy of 91.2% with an F1-score of 0.9091. The proposed framework that presents the reliable and scalable method for improving the efficiency of the early MDD diagnosis. The final feature set is fed into an MLP classifier. The proposed method's performance is benchmarked against conventional models, including Support Vector Machines (SVM), K-Nearest Neighbors (KNN), XGBoost, and Logistic Regression. Evaluation metrics—accuracy, precision, recall, and F1-score—demonstrate the robustness and reliability of the CNN- MLP model, highlighting its potential as a scalable solution for precise and data-driven mental health evaluation.**

***Index Terms*— MDD detection, Hybrid Deep Learning, CNN, MLP, Feature Engineering, Dimensionality Reduction, NHANES, Mental Health Analytics.**

I. INTRODUCTION

A common mental health condition is the psychiatric illness that profoundly affects the emotional regulation and physical health. Characterized by persistent low mood, a loss of interest in daily activities. So, it can lead to fatigue, disruptions in sleep and eating habits, and difficulty in concentration. These symptoms can drastically impair an individual's daily func- tioning. Depressive disorders are a major public health issue worldwide, affecting individuals of all ages and backgrounds. These conditions are typically marked by ongoing feelings of sadness, loss of interest in everyday activities, low energy, and diminished cognitive abilities.
Nowadays, the diagnosis of MDD is challenging for each individuals. Due to the limitations of lack of diagnosis toolsin medical health centres. It is very difficult to correctly predict the disease. Existing methods is conversation between professionals and patients will be helps to identify specific symptoms. But, it's not properly detected. Each professionals can interpret differently it will causes misdiagnosis. In recent years, researchers will focusing to identify the symptoms in each person correctly using advanced techniques without misdiagnosis.

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Traditional methods is diagnosing the depression which relies on heavily the clinical interviews and self-reported questionnaires. While widely used, these approaches are in- herently subjective and may lead to inconsistencies due to individual differences in symptom expression, patient honesty, and clinician interpretation. Moreover, the lack of objective biomarkers for depression will makes more complication to achieving the timely and accurate diagnosis. In this study, a deep learning-based framework is proposed for solving the addressing issues to the diagnosis of MDD. The main aim is to build an efficient and personalized model that can distinguish between depressed and non-depressed individuals. The proposed system aims to assist healthcare clinicians.

II. RELATED WORKS

Recent advancements in the machine learning and deep learning have helped to detect and diagnosing the complex disorder. Y. Kong et al. [1] addresses the issue is the interview between professionals an patients will be make the results as high misdiagnosis rates due to the complexity of the disorder and patients disease variability. The need of the medical diagnostic tools which increases misdiagnosis of MDD. So, such issue is solved to introducing a framework called Multi- stage Graph Fusion Networks which will diagnose the disorder accurately. Initially, calculating the functional connectivity to capturing the interactions between white and gray matter, then deep subspace learning model is used to extract the multi-stage features and constructs the graphs.

Finally, Integrate both to performing accurately.Kong et al. [2] emphasizes the complexity of diagnostic effectiveness and existing methods will fail to utilizing the temporal properties of functional connectivity and fuse it into the multi-connectivity information. According to solve the issue by proposing the framework is Multi-Connectivity Representation Learning Network is focuses on integrating the brain activity. Firstly computing the structural, static functional and dynamic functional graphs from the MRI data and developing the Structural-Functional Fusion module to decouple graph convolution. Then, design Static Dynamic Fusion module to enhance the MDD diagnosis. J. Kim et al. [3] address the problem is evaluating the depressive mood for the better diagnosis rate and giving proper treatment. The proposed model will analyze the relationship between the scores of depressive mood and locomotor activity in MDD patients and healthy controls is measured by using wearable devices.

T. Zhao and G. Zhang [4] discuss the model will face the challenges is neglecting the dynamic brain network and perfor- mance is also poor with small datasets. The main problem is diagnosis issue using fMRI data. So, solving these addressed issues using Dynamic-static Fusion Graph Neural Networks. Initially both static and dynamic brain networks model using graph isomorphism encoder and achieving effective fusion of temporal and spatial information using spatiotemporal atten- tion mechanism. Finally, integrate causal disentangling module and an orthogonal regularization module to improving model's performance.

C. Greco, O. Matarazzo, G. Cordasco, A. Vinciarelli, Z. Callejas, and A. Esposito [5] discuss challenge in diagnosing Major Depressive Disorder (MDD) and its subtypes due to the limitations of traditional assessments and self-reported measures This has emphasized the need for incorporating objective biomarkers, such as electroencephalography (EEG) features, to improve early detection and prevent the worsening of symptoms. To address this issue, a systematic review was conducted, involving a comprehensive search of Scopus, PubMed, and Web of Science databases, following PRISMA guidelines. From an initial set of 1,871 articles, 76 rele- vant studies were identified, confirming that EEG measures are effective in differentiating between healthy individuals and those with depression. The review also highlights the importance of further research into the causal relationship between EEG measures and depressive subtypes. Although the review presents promising findings, it identifies key gaps in the existing literature, such as the lack of understanding of the causal link between EEG measures and depressive subtypes, as well as various methodological issues that need to be addressed to improve the reliability and validity of future studies in this field.

X. Yuan et al. [6] discuss the significant challenges in accurately diagnosing Major Depressive Disorder (MDD) at an individual level, particularly due to the clinical heterogene- ity of the disorder and the decreased accuracy when using multisite data. Traditional methods often fail to account for the variability introduced by different data sources, leading to reduced diagnostic reliability. To address these issues, the Brain Dynamic Attention Network (BDANet) framework was introduced. BDANet incorporates a Dynamic BrainGraph Gen- erator that effectively highlights and represents the topological relationships between Regions of Interest (ROIs), overcoming the limitations of static methods. The framework achieved an 81.6% accuracy in diagnosing MDD. The primary gap iden- tified remains the challenge of accurately diagnosing MDD in the face of its clinical heterogeneity and the variability introduced by multisite data, which continues to affect identi- fication accuracy.

A. O. Khadidos, K. H. Alyoubi, S. Mahato, A. O. Khadidos, and S. N. Mohanty [7] address the identification of depressive disorder due to the limitations of available laboratory tests and focusing to develop the portable and accurate framework for detecting the depression using EEG channels and achieving an accuracy of 91.74%. The problem is lack of cost effective tool also causing misdiagnosis of disorder. So, the model will select the specific brain regions and EEG features to identify minimum no of channels for increasing accuracy of detection.

M. Xia, Y. Zhang, Y. Wu, and X. Wang [8] present a solution to the significant challenge of accurately diagnosing Major Depressive Disorder (MDD), particularly when tradi- tional methods fail to fully exploit brain connectivity features derived from resting-state electroencephalography (EEG) data. To address this, they developed a deep learning model that integrates a multi-head self-attention mechanism to automat- ically learn potential connectivity relationships among EEG channels. The model also incorporates a parallel two-branch convolutional neural network (CNN) to extract higher-level features, with a fully connected layer for classification. This approach achieved an impressive 91.06% accuracy, effectively distinguishing between MDD patients and healthy controls based on EEG data, surpassing existing methods.

Y. Wang et al. [9] explore the difficulties of diagnosing Major Depressive Disorder using EEG signals and issue of data quality from noisy EEG recordings and data size limi- tations which causes overfitting in the deep learning models. The proposed framework is Diffusion-Based Deep Learning model. So, this model have two partition : the first partition is Forward Diffusion Noisy Training module will extracting the noise irrelevant features from noisy EEG data and the second partition is reverse Diffusion Data Augmentation module is helping to reduce the overfitting risk.

B. Zhang et al. [10] explore the challenges of analyzing and classifying the MDD using EEG data. The traditional EEG nased MDD classification methods will failure to consider the interconnections of EEG electrodes. The proposed model is brain functional network framework to analyze and classify MDD using EEG dat. Initially, Phase Lag Index is constructed from 64 channel resting state EEG and analyze the statistical analysis to identify changes.

III. METHODOLOGY

A deep learning-based multi-stage model is shown in fig. 1. is proposed to enhancing the diagnosis of Major Depressive Disorder. The framework has several stages as data preprocessing, feature extraction, dimensionality reduction, and classification. Initial process is preproces the data addresses missing values, convert the categorical data to numerical format and applies feature normalization, and divides the data into training and testing subsets. A one-dimensional convolutional neural network is utilizing to automatically extracting the spatial features. Dimensionality reduction involves selecting the important 300 features using SelectKBest, followed to reduce it into 150-dimensional space using the method Principal Component Analysis (PCA). Classification is conducted using a Multi-Layer Perceptron classifier dropout to mitigate overfitting. The model's effectiveness is measured using evaluation metrics such as accuracy, precision, recall, and F1-score.

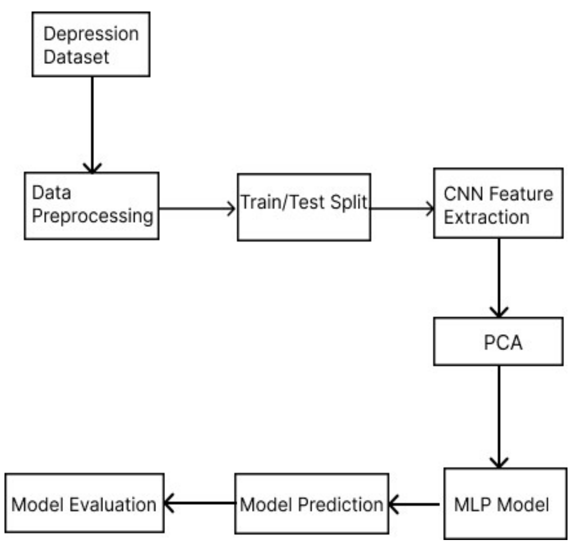

Fig. 1. System Design

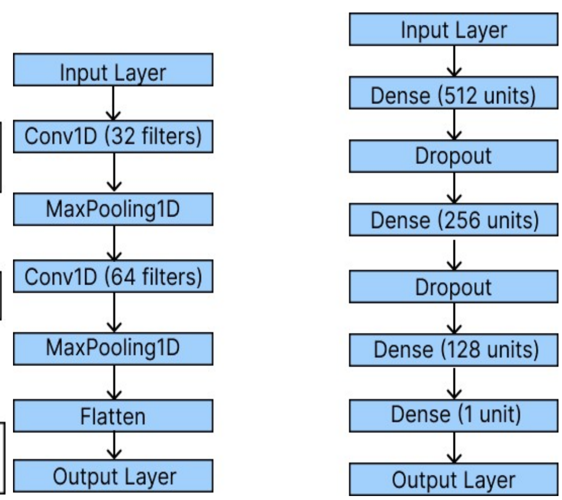

Fig. 2. CNN AND MLP Model

A. Depression Dataset

This study utilizing the data from the National Health and Nutrition Examination Survey (NHANES), which is publicly available resource that will provides the clinical and demo- graphic health information. The dataset includes sleep patterns, physical activity, heart rate, cholesterol levels, body mass index (BMI), blood pressure, pulse rate, and psychological assessment responses. The dataset is employed whcih con- tains 1,817 samples and 491 features, with a total size of approximately 2.65 MB. Totally, 1,709 samples are catego- rized as non-depressed, and 108 are classified as depressed, reflecting a common class imbalance in mental health datasets. So, the dataset is balanced by using random under-sampling technique.

B. Data Preprocessing

Preprocessing the data is the important step to removing the impurities from the dataset for training the machine learning models. The dataset contains the missing values is the common issue. and includes the both numerical and categorical data are converted into the numerical from using one-hot encoding and label encoding. Then all the numerical features to similar scale using normalization techniques such as min-max scaling and also balancing the dataset to improving the efficiency of the model.

C. Train/Test Split

After preprocessing the data, the dataset will splits it into two : training and testing. So, 70% of the dataset is used for training the data and remaining 30% for testing, which will evaluates the model's performance and helps to detect overfitting.

D. CNN Feature Extraction

The proposed system employs a 1d convolutional neural network is shown in fig. 3. to identify the features from reprocessed data. And applying the max pooling operations to reduce the dimensionality of the features. Then, applying Rectified Linear Unit (ReLU) activation is applied to introduce non-linearity. The first convolutional block consist of 32 filters with kernel size is 3 and stride is 1 followed by pooling layer.

Model: "sequential_1"

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 512)	77,312
dropout (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 256)	131,328
dropout_1 (Dropout)	(None, 256)	0
dense_2 (Dense)	(None, 128)	32,896
dense_3 (Dense)	(None, 1)	129

Total params: 241,667 (944.02 KB)
Trainable params: 241,665 (944.00 KB)
Non-trainable params: 0 (0.00 B)
Optimizer params: 2 (12.00 B)

Fig. 3. CNN

Next, second block is applied with the 64 filters. After resulting feature maps are flattened into 1d vector for classification. The overall trainable parameters is 6000, efficient training and capturing meaningful representation from the data.

E. Feature Selection

After extracting the features using CNN, then applying the feature selection method using SelectKBest for increasing the efficiency of the model. So, feature selection will using to select the most important 3features for next feature reduction for better performance of MDD classification.

Feature Reduction

After the feature selection, then applying the PCA method to improving the accuracy of the model and reducing the dimensionality. So, the PCA will reduce the 300 features as 150 features to capturing the most significant features from the dataset. The purpose of using this method to reducing the complexity of the model and make the model be more accurate diagnosis of depression cases.

MLP Model (Multi-Layer Perceptron Classi- fier)
To perform binary classification, a Multi-Layer Perceptron is shown in fig. 4.employed following a flattening an extracted features.

Model: "sequential_1"

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 512)	77,312
dropout (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 256)	131,328
dropout_1 (Dropout)	(None, 256)	0
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Total params: 241,667 (944.02 KB)
Trainable params: 241,665 (944.00 KB)
Non-trainable params: 0 (0.00 B)
Optimizer params: 2 (12.00 B)

Fig. 4. MLP

The network comprises three dense layers, each followed by dropout layers to mitigate overfitting. The first dense layer contains 512 units and is followed by a dropout rate of 0.5. This is succeeded by a second dense layer with 256 neurons and an identical dropout setting. The third layer includes 128 neurons, leading to a final output layer consisting of a single neuron activated via a sigmoid function to enable binary output—indicating depressive or non-depressive status. The model will be trained using an Adam optimization algorithm with the learning rate is 0.001 and the binary cross-entropy will serves as loss function. The training is conducted over the 50 epochs and batch size is 32. In total, model contains approximately 241,667 trainable parameters, balancing model complexity and computational cost. plot the accuracy of the model is shown in fig. 5. and also plot the loss curve in fig. 6.

Model Prediction
The MLP model has been trained and evaluated on the test dataset to produce predictions. For each individual, the model generates a probability score that reflects the likelihood of having Major Depressive Disorder (MDD). A predefined threshold, typically set at 0.5, is then used to categorize the results: individuals with a probability above this threshold are classified as MDD-positive, while those with a probability below the threshold are labeled MDD-negative.

Model Evaluation

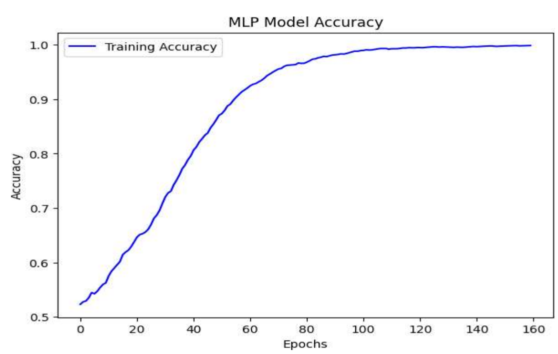

Fig. 5. MLP Model Accuracy

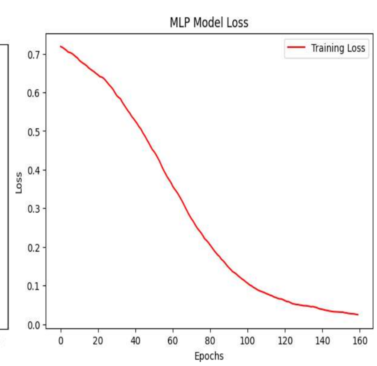

Fig. 6. MLP Model Loss

Finally, The proposed framework will be evaluated using the evaluation metrics.So, the model’s performance is achieving the accuracy is 91.2% than the other classifiers such as SVM, KNN, XGBoost and Logistic Regression. Then the additional metrics as precision, recall, F1 score, sensitivity and specificity. The F1-score will providing the balance between precision and recall, combining them into a single metric. Sensitivity and specificity evaluate the model's accuracy in identifying positive and negative cases, respectively. The consistently strong results across all metrics indicate that the model is both reliable and effective in diagnosing Major Depressive Disorder.

F. Experimental Results

To assess the proposed classification framework's perfor- mance, several machine learning models were compared, with the Multi-Layer Perceptron (MLP) chosen as the benchmark. The model is evaluated using metrics such as accuracy, F1- score, sensitivity and specificity. The MLP, a type of feed- forward neural network designed to learn complex, non-linear patterns, served as the core classifier. Among the evaluated models, the MLP achieved superior results as an accuracy of 91.2%, F1 score is 0.9091, sensitivity is 0.9796 and specificity is 0.9444. So, this will highlights the better model's perfor- mance to detect both the depressive cases and non-depressive cases based on the analysis. Then, MLP will outperforms all other models based on classification effectiveness. The result of base model MLP is compared with other models as SVM, KNN, XGBoost, Logistic Regression. The comparative analysis give better results is shown in fig. 7. MLP is more accurate than the other models.

MODEL PERFORMANCE COMPARISON

	Model	Accuracy (%)	F1 Score	Sensitivity (Recall)	Specificity
0	MLP	91.2	0.9091	0.8796	0.9444
1	SVM	86.57	0.8626	0.8426	0.8889
2	KNN	72.69	0.6335	0.4722	0.9815
3	XGBoost	88.89	0.88	0.8148	0.963
4	Logistic Regression	87.96	0.8738	0.8333	0.9259

Fig. 7. Model Performance Comparison

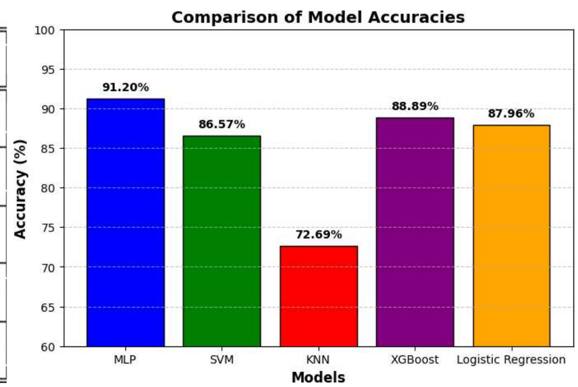

Fig. 8. Model Accuracies

Then, plot the accuracy of the classifiers is shown in fig. 8.

IV. CONCLUSION

In conclusion, this paper introducing a deep learning-based framework for increasing the accuracy of the model reducing the misdiagnosis of depression cases. So, the framework will combines the CNN for extraction of features. Then, applying feature selection using SelectKBest method and then applies feature reduction using the PCA for increasing the accuracy of the model. After that final classification using MLP classifiers for prediction. The model achieves 91.2% accuracy and outperforming than other classifiers such as SVM, KNN, XGBoost and Logistic Regression. This will helps to assist clinicians in early diagnosis and personalized effective treatment planning. Future works will be focusing to incorporating additional data sources and exploring the advanced techniques to improving predictive performance.

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