© October 2024 | IJIRT | Volume 11 Issue 5 | ISSN: 2349-6002

Mental Illness Detection Using Deep Learning Models*

[1]Rishabh Saxena, [2]Keshav Sharma, [3]Sheenam Naaz
[1,2,3] Dept. of Computer Science and Engineering Sharda University Greater Noida, India

***Abstract*—Because mental health illnesses are becoming more common and early diagnosis is crucial, detecting mental disease has become a key challenge in modern healthcare. In this study, the MOMDA dataset is used, which includes both voice recordings and EEG signals, to diagnose mental diseases using deep learning techniques. Since voice and speech patterns might offer valuable insights into an individual's mental health, we are primarily focused on the audio dataset. We want to assess audio cues that correspond with different mental health disorders using cutting-edge deep learning models, providing a scalable, effective, and non-invasive method of mental health screening. Because it offers personalized treatment plans, ongoing monitoring, and early identification, this approach has the potential to completely transform mental health diagnostics.**

***Index Terms*—Deep Learning, Artificial Neural Network, Audio Pattern, Audio Processing**

I. INTRODUCTION

Millions of people worldwide suffer from mental health illnesses including bipolar disorder, depression, and anxiety, and many of these instances go misdiagnosed since there aren't enough reliable screening methods. Traditional diagnostic procedures rely mainly on subjective judgments by mental health experts, which may lead to delayed diagnosis and uneven treatment. The emergence of deep learning presents a chance to create automated systems that can identify tiny speech patterns that point to mental health problems.

In this study, we investigate the potential of audio-based deep learning models for mental disease identification using the MOMDA (Multimodal Open Dataset for Mental Disorder Analysis) dataset, which contains both audio and EEG data. With an emphasis on the audio dataset, our goal is to discover indicators of mental health illnesses by extracting attributes including pitch, tone, speech pace, and emotion. The audio data will be processed using deep learning models, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), to categorize people according to their mental health condition. This method offers a more approachable option for early intervention and widespread mental health screening by improving the precision and effectiveness of mental disorder identification.

II. LITERATURE SURVEY

This paper explores the use of BERT-based classifiers for early detection of self-harm and depression severity, achieving high performance in Task 1 with a precision of up to 91.3 percent and suggesting potential future applications in detect- ing other mental health conditions like anorexia and suicide [1]. Another paper presents a novel neural network model for analyzing audio signals from interviews to detect stress levels and differentiate mental disorders, enhancing prior frameworks with deep feature extraction [2]. This study proposes an adversarial inference approach to person identification using EEG data, improving session-invariant, person-discriminative representations for more robust, longitudinal usage [3]. This paper discusses the development of bioinspired intelligent systems for biodiversity conservation, introducing alternative techniques that diverge from mainstream artificial intelligence approaches [4]. another research provides an overview of deep learning applications in EEG, reviewing its progress and categorizing applications into brain-computer interfaces, disease detection, and emotion recognition, while discussing future challenges and opportunities [5].

This paper presents a computer-aided diagnosis system for major depressive disorder (MDD) using a non-invasive device that collects EEG signals and employs a convolutional neural network (CNN) for real-time classification. The system uses an asymmetry image matrix based on EEG power values to distinguish between healthy individuals and those suffering from depression [6]. This study explores the use of deep convolutional networks (ConvNets) for end-to- end EEG analysis, achieving improved decoding performance compared to traditional methods. It highlights the ability of ConvNets to learn informative EEG features without relying on handcrafted ones and emphasizes advanced visualization techniques for better understanding of these features [7]. Another paper discusses automated detection methods for depression through language analysis, comparing hybrid and ensemble classifiers. The results indicate that ensemble models outperform hybrids, suggesting that multiple feature combina- tions enhance detection performance [8]. Lastly, a multimodal deep learning framework that extracts features from speech samples to predict mental disorders, including depression and bipolar disorder. By combining various pre-trained models and utilizing transfer learning, the approach demonstrates that accurate predictions can be achieved through multimodal analysis of clinical interviews [9]. Another review discusses the use of EEG signals to detect depression, highlighting their potential as a non-invasive, real-time diagnostic tool. It notes that current diagnostic methods rely on self-reporting, which can be subjective. Although EEG shows promise for depression detection, further research is required to develop a reliable diagnostic tool[10]. Another paper highlights the growing impact of mental illnesses as the modern workforce shifts from physically to mentally demanding tasks, empha- sizing the increasing strain on mental health. It suggests that more attention is needed in this area. The study surveys papers that explore using audio features to build machine learning models for predicting mental illnesses [11]. Another Research explores the automated detection of depression using facial expressions, addressing the growing concern over mental illness. Their method, ADDMIL, achieved 74.7 accuracy and 74.5 recall, surpassing the baseline by over 10 and improving upon existing MIL-based methods [12]. A study focuses on the use of machine learning and deep learning methods for diagnosing mental illnesses like schizophrenia, depression, anxiety, bipolar disorder, PTSD, anorexia nervosa, and ADHD. Using the PRISMA methodology, 33 articles were reviewed and classified based on the disorders they addressed. The study highlights the growing role of these technologies in healthcare, both for diagnosis and predicting treatment outcomes [13]. Another paper presents a systematic review of the use of deep learning for EEG classification, aimed at enhancing the practical application of EEG by reducing dependence on trained professionals. The review addresses critical questions such as the types of EEG classification tasks explored, input formulations for training deep networks, and task-specific deep learning structures [14]. This study addresses the global concern of mental illness by introducing a novel system for detecting mental disorders through facial expression analysis. Using the AffectNet and FER 2013 datasets, the research proposes a hybrid architecture for diagnosing conditions like depression and anxiety. The system leverages the YOLOv8 object detection algorithm, combined with an ensemble clas- sifier that fuses Convolutional Neural Networks (CNNs) and Visual Transformer (ViT) models, achieving an accuracy of around 81 percent [15].

III. METHODOLOGY AND IMPLEMENTATION

One approach is to use a case specific CNN model that can be trained over the MOMDA dataset. The dataset give two major attributes – audio recordings of patients and electroen- cephalogram. Please note that, There is no single algorithm that can perfectly predict the behavior of any individual, let alone a group of people with mental illness. However, there are a number of different approaches that can be used to develop algorithms that can improve the accuracy of behavior prediction.

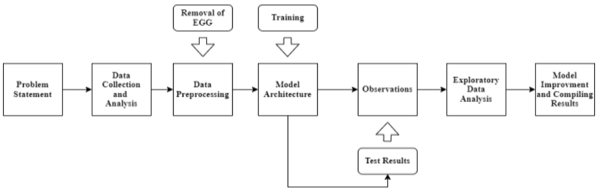

Fig. 1. Methodology

- Data Preprocessing: The implementation is to only take into account the audio information of the dataset and so we have disregard the EEG information for each datapoint
- Training and Testing: The model will be put through the section of the data meant for training and when done, the model will be run for a small ammount of predicted values and be compared to the test data.
- EDA: Using the Accuracy scores and such, we will be able to understand where the model is lacking in performance.

A. *Dataset*

The MOMDA dataset comprises data collected from par- ticipants diagnosed with depression and healthy controls in three different experiments. All participants provided informed consent, and the study was approved by the local Ethics Committee at Lanzhou University Second Hospital, adhering to the World Medical Association’s Declaration of Helsinki [21]. Following are details on the dataset

- 110 participants in total.
- 73 outpatients diagnosed with depression (44 males and 29 females; aged 16–56). 87 healthy controls (59 males and 28 females; aged 18–55).

This dataset is designed to support research in detecting depression through EEG and speech analysis, providing both brain activity and spoken language data from depressed pa- tients and healthy individuals.

B. Model Architecture

Following are the characteristics of the model that make it more suitable for the application –

- Increased Depth: The architecture has 3 Conv1D layers), with an increasing number of filters (64 → 128 → 256), allowing for progressively deeper feature extraction.
- Pooling and Dropout: After each convolutional block, there are dropout and max-pooling layers, indicating the model is designed to avoid overfitting while focusing on the most salient features.
- Classification Head: The Flatten, Dense, and Softmax layers form the classification part of the network, where high-level features are used to classify the input data into different categories.

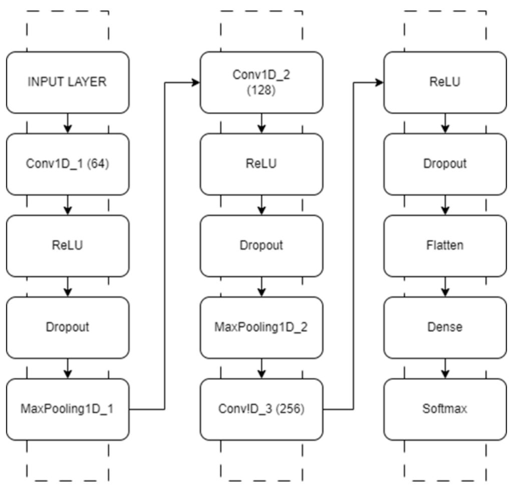

Fig. 2. Model Architecture

TABLE I
MODEL LAYERS AND FUNCTIONS

Layer/Function	Description
Input Layer	Receives input data for the model.
Conv1D	Applies 1D convolution filters to extract features from sequential data.
ReLU Activation	Introduces non-linearity into the model after each convolutional layer.
Dropout	Randomly drops neurons during training to prevent overfitting.
MaxPooling1D	Downsamples the input by taking the maximum value over a window to reduce size.
Flatten	Converts 1D feature maps into a 1D vector before fully connected layers.
Dense Layer	A fully connected layer used to combine extracted features for classification.
Softmax Layer	Outputs a probability distribution over multiple classes for classification.

IV. RESULTS

The model was trained over 80 epochs and had dropout function intergrated into it, which would likely decrease the overfitting accuracy of the model. On average the model gives

TABLE II
METRIC RESULTS OF THE MODEL

Class	Precision	Recall	F1-score
“Healthy” (1)	0.81	0.64	0.71
“Depressive” (0)	0.78	0.80	0.79

an accuracy of 75.6 percent over the testing data. while the accuracy may seem low at first glance, it is as such due to fact that model’s dropout function stops the model from achieve extremely high accuracies as to suggest over fitting. As per the given confusion matrix, 40 is the highest accuracy level and is only achieved for the “depressive” state of the patient. The mental illness detection model is built well and ready for use with the aim of real time emotion identification, efficiency, and privacy in human computer interaction. The prime motive is to enhanced communication technologies and emotions associated with AI systems as it accepts emotions through voices with superior deep learning algorithms.

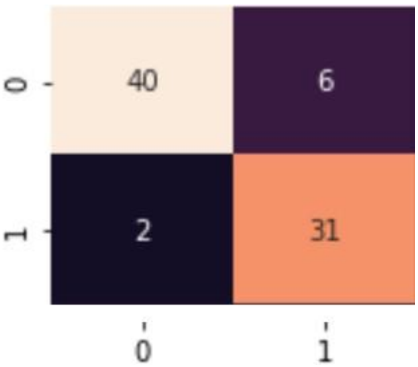

Fig. 3. Confusion Matrix

V. FUTURE SCOPE

Future applications of mental health detection systems hold great potential for transforming the way mental health disor- ders are diagnosed and monitored. A key development in this area would be the integration of real-time detection methods that utilize both audio input and electroencephalogram (EEG) signals. By combining these two modalities, researchers and clinicians can gain a more holistic view of a patient's mental health status. Audio-based detection, through speech analysis, could reveal stress levels, emotional states, and other indicators of mental disorders, such as depression or schizophrenia, by analyzing tone, pitch, and linguistic patterns. When combined with EEG data, which captures electrical activity in the brain, this approach can offer a deeper understanding of cognitive and emotional states. The synergy of these technologies could enable real-time mental health monitoring in both clinical settings and remote environments, potentially offering early detection of issues like depressive episodes, anxiety, or even cognitive decline.

VI. CONCLUSION

The prime motive of the system is to upgrade communica- tion with mental health in AI systems as it accepts emotions through voices with superior deep learning algorithms. One major observation from this process has been the need to pay close attention to data conditioning and model stability in emotional detection across languages and accent. Furthermore, handling of issues such as overfitting, data unbalanced, and privacy concerns especially when working with applications that involves people's emotions.

REFERENCES

[1] Mart´ınez-Castan˜o, Rodrigo, et al. "BERT-based transformers for early detection of mental health illnesses." Experimental IR Meets Multilin- guality, Multimodality, and Interaction: 12th International Conference of the CLEF Association, CLEF 2021, Virtual Event, September 21–24, 2021, Proceedings 12. Springer International Publishing, 2021.

[2] Karmore, Pravin, Swapnili Karmore, and Satyajit Uparkar. "Mental Ill- ness Detection Through Audio Signal Processing." Bioscience Biotech- nology Research Communications 13.14 (2020): 305-309.

[3] O¨ zdenizci, Ozan, et al. "Adversarial deep learning in EEG biometrics." IEEE signal processing letters 26.5 (2019): 710-714.

[4] Pereira, Lucas, and Antonio G. Ravelo-Garc´ıa. "Highlights of ES2DE and IWOBI 2017: extended versions of selected best papers." Computing 100 (2018): 1133-1135.

[5] Gong, Shu, et al. "Deep learning in EEG: Advance of the last ten- year critical period." IEEE Transactions on Cognitive and Developmental Systems 14.2 (2021): 348-365.

[6] Anand, Abin B., et al. "Computer Aided Diagnosis of Depression Using EEG Signal Processing." 2023 Annual International Conference on Emerging Research Areas: International Conference on Intelligent Systems (AICERA/ICIS). IEEE, 2023.

[7] Schirrmeister, Robin Tibor, et al. "Deep learning with convolutional neural networks for EEG decoding and visualization." Human brain mapping 38.11 (2017): 5391-5420.

[8] Ansari, Luna, et al. "Ensemble hybrid learning methods for automated depression detection." IEEE transactions on computational social sys- tems 10.1 (2022): 211-219.

[9] Naderi, Habibeh, Behrouz Haji Soleimani, and Stan Matwin. "Multi- modal deep learning for mental disorders prediction from audio speech samples." arXiv preprint arXiv:1909.01067 (2019).

[10] Babu, Nirmal Varghese, et al. "AI Based EEG Analysis for Depression Detection: A Critical Evaluation of Current Approaches and Future Di- rections." 2023 International Conference on Computational Intelligence and Sustainable Engineering Solutions (CISES). IEEE, 2023.

[11] Hingorani, Manan, and Nitin Pise. "Detection of mental illness using machine learning and deep learning." Proceedings of the international

conference on industrial engineering and operations management. Mon- terrey, Mexico: IEOM society international. 2021.

[12] Shangguan, Zixuan, et al. ”Dual-stream multiple instance learning for depression detection with facial expression videos.” IEEE Transactions on Neural Systems and Rehabilitation Engineering 31 (2022): 554-563.

[13] Iyortsuun, Ngumimi Karen, et al. ”A review of machine learning and deep learning approaches on mental health diagnosis.” Healthcare. Vol.11. No. 3. MDPI, 2023.

[14] Craik, Alexander, Yongtian He, and Jose L. Contreras-Vidal. ”Deep learning for electroencephalogram (EEG) classification tasks: a review.” Journal of neural engineering 16.3 (2019): 031001.

[15] Aina, Joseph, et al. ”A Hybrid Learning-Architecture for Mental Disor- der Detection Using Emotion Recognition.” IEEE Access (2024).

[16] Park, Dabin, et al. ”Probability-based multi-label classification consider- ing correlation between labels–focusing on DSM-5 depressive disorder diagnostic criteria.” IEEE Access (2024).

[17] Gunduz, Hakan. ”Deep learning-based Parkinson’s disease classification using vocal feature sets.” Ieee access 7 (2019): 115540-115551.

[18] Xia, Min, et al. ”An end-to-end deep learning model for EEG-based ma- jor depressive disorder classification.” IEEE Access 11 (2023): 41337-41347.

[19] Ahmed, Sabbir, et al. ”Taking all the factors we need: A multimodal depression classification with uncertainty approximation.” IEEE Access 11 (2023): 99847-99861.

[20] Xia, Min, et al. ”An end-to-end deep learning model for EEG-based ma- jor depressive disorder classification.” IEEE Access 11 (2023): 41337-41347.

[21] Cai, Hanshu, et al. ”A multi-modal open dataset for mental-disorder analysis.” Scientific Data 9.1 (2022): 178.