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Research paper

Leveraging Deep Learning for Enhanced Classification of Depression Via EEG-Derived Imagery

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Abstract

Depression is the most prevalent psychological disorder worldwide, affecting individuals irrespective of age and frequently associated with underlying organic etiologies. Its influence extends beyond psychological health, exerting significant effects on physical well-being as well. Clinically, depression is recognized as a neuropsychiatric condition linked to alterations in the brain's neurochemistry, with its pathogenesis involving a complex interaction among biological, genetic, psychological, and environmental determinants. In this study, we developed a deep learning-based approach for the classification of depression using electroencephalogram (EEG)-derived imagery. Specifically, the ResNet50V2 convolutional neural network architecture was employed to differentiate between EEG images of healthy controls and those diagnosed with Major Depressive Disorder (MDD) based on standard diagnostic criteria. A meticulously curated dataset comprising pre-processed EEG images from both cohorts was used to train the model. Transfer learning was applied by leveraging the pretrained ResNet50V2 weights from the ImageNet dataset, facilitating efficient feature extraction tailored for the EEG domain. The model's performance was evaluated using multiple quantitative metrics, achieving a classification accuracy of 97.25%, indicating high discriminative capability. These findings demonstrate the potential of deep learning models, particularly ResNet50V2 with transfer learning, for the reliable detection of depression from EEG images, which may support timely diagnosis and intervention in clinical settings.

Keywords: *Deep Learning; Electroencephalogram (EEG); Major Depressive Disorder; Resnet50V2; Transfer learning.*

1. Introduction

A common mental disorder in which millions of people globally suffer is depression. It is characterized by a lingering sense of melancholy, pessimism, and a lack of interest in or enjoyment of enjoyable activities. [1]. People with depression often experience a range of symptoms [2] that can vary in severity, changes in eating and sleep patterns, poor energy, trouble focusing, feelings of shame or unworthiness, and even suicidal or death thoughts.

1.1. Various Causes and Aftereffects of Depression

A complex interaction of psychological, social, ecological, and genetic [3] variables leads to depression, often involving a combination of these influences. Biological factors include imbalances in neurotransmitters [4] such as serotonin [5] and norepinephrine [6], as well as changes in brain structure [7] and function. Additionally, there is a genetic component because people who have a family history of depression are more likely to experience it. Psychological factors [8] encompass personality traits, low self-esteem, and negative thinking patterns.
Figure 1 illustrates the common clinical signs and symptoms of depression.

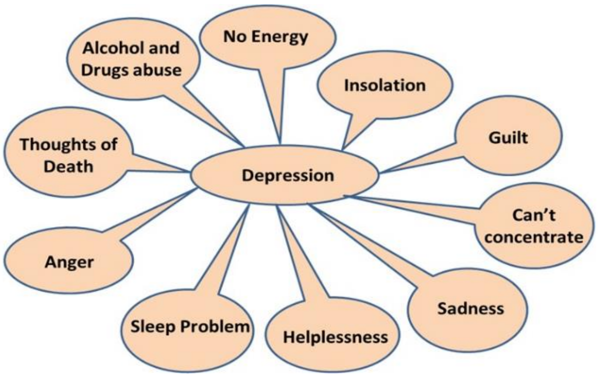

Fig. 1: Pictorial Depiction of Depression Symptoms and Signs.

Environmental triggers such as trauma, chronic stress, loss, or significant life changes can contribute to the development of depression. Additionally, certain medical conditions, substance abuse, and hormonal imbalances [9] can increase susceptibility. Understanding these interrelated causes helps identify and address the underlying factors, paving the way for effective treatment and prevention strategies.
Although the signs and symptoms of depression [10] can vary from person to person, they often involve constant feelings of gloom, despair, or emptiness. Additionally, individuals may experience a loss of interest or enjoyment in activities once enjoyed, changes in weight and eating habits, trouble sleeping, fatigue or diminished energy, difficulty in paying attention or making decisions, feelings of shame or vanity, irritability or restlessness, physical symptoms [11] like headaches or digestive issues, and recurrent thoughts. It's important to note that experiencing several of these symptoms for an extended period of time may indicate the presence of depression, and seeking professional help is recommended.
The aftereffects of depression may manifest as social withdrawal, strained relationships, difficulty concentrating or making decisions, decreased productivity, and a decline in overall physical and mental well-being [12]. Sleep disturbances, appetite changes, and fatigue are common, further exacerbating the burden. Depression can impair daily functioning, hinder personal and professional growth, and even increase the risk of self-harm or suicide [13]. Seeking timely support and treatment is crucial to mitigating the long-term effects of depression and enhancing one's quality of life.

1.2. Types of Depression

Depression encompasses various types, each characterized by unique features. MDD is the most common form, involving persistent and severe depressive symptoms. PDD, 14 previously known as dysthymia, involves chronic low-grade depression lasting for extended periods. SAD occurs seasonally, typically during winter, and is associated with changes in light exposure. PPD affects women after childbirth, leading to intense sadness and exhaustion. Bipolar disorder involves alternating episodes of depression and mania. Psychotic Depression combines depressive symptoms with psychosis, such as hallucinations or delusions. Atypical Depression is characterized by mood reactivity, increased appetite, hypersomnia [15], and a feeling of heaviness in limbs. Catatonic depression is a subtype where individuals exhibit symptoms of catatonia alongside depression [16]. Understanding these distinct types helps inform diagnosis and guide appropriate treatment strategies for individuals affected by depression. Figure 2 depicts different types of depression.

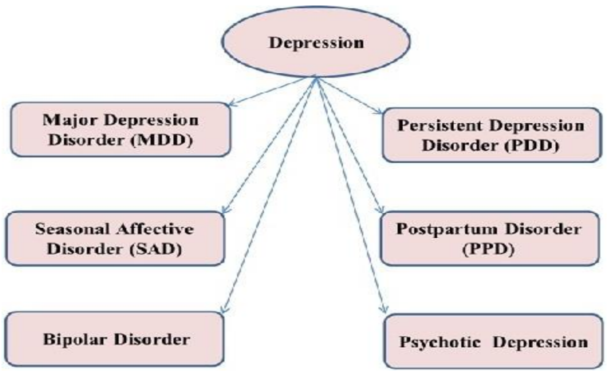

Fig. 2: Types of Depression.

2. Literature Review

2.1. Machine Learning Based Approaches

Priya et al [20] proposed a method for predicting depression utilizing various machine learning (ML) algorithms. With the use of a questionnaire, information was acquired from both employed and unemployed people from a variety of cultures and communities. Among the five algorithms employed, the Random Forest classifier demonstrated the highest accuracy, indicating its effectiveness in predicting these mental health conditions based on the collected data.
Kumar et al. [21] presented an approach to predict psychological problems like anxiety, depression, and stress using eight ML algorithms. The dataset for analysis was obtained from the online DASS42 tool, and a hybrid approach was implemented to predict the severity levels of these mental health conditions. The DASS21 dataset was also subjected to the same analysis techniques. The hybrid algorithm yielded higher prediction accuracy compared to individual algorithms, but the type of neural network used achieved the highest accuracy. However, it was worth noting that the hybrid approach required longer execution times, ranging from 30 to 45 minutes, while individual algorithms executed within a maximum of five minutes.

Sau et al. [22] highlighted the significance of ML in automating the screening process for mental health disorders. The study compared the effectiveness of various ML algorithms for detecting anxiety and sadness among seafarers. The study utilized five ML classifiers implemented with Python programming. This technological approach successfully replaced the manual depression detection methods with a computer-based analysis technique. The results demonstrated that the accuracy achieved by the ML algorithms was sufficient for effective screening purposes, providing a valuable alternative to the traditional screening methods.
Li et al [23] aimed to improve the recognition of depression by leveraging the transformation of EEG features and ML techniques. They experimented using a face stimuli task and recorded the EEG data of twenty-eight subjects using a 128-channel setup. The original features were extracted by applying the Auto-regress model for power spectral density and the Hjorth algorithm for activity, using different time windows. To incorporate spatial information from the EEG caps, the authors employed image conversion and utilized a convolutional neural network (CNN) in their DL approach for recognition. Both approaches were evaluated across individual and combined frequency bands, allowing a thorough assessment of depression detection performance.McGinnis et al. [24] introduced a novel method for identifying internalizing disorders in young children through a brief 3-minute speech task. The study demonstrated that by analyzing audio data from the task using ML techniques, it was possible to accurately identify children with internalizing disorders with an accuracy of 80%. This approach provides a promising avenue for early detection and intervention in young children with internalizing disorders, offering the potential for improved mental health outcomes.

2.2. Deep Learning Based Approaches

Mumtaz et al [25] introduced two DL architectures, the one-dimensional DCNN and the one-dimensional DCNN with LSTM architecture. These structures were created to automatically recognize EEG data patterns that may be used to categorize people as sad or healthy controls. Using resting-state EEG data gathered from 33 depressive individuals and 30 normal controls, the suggested models were verified. The visual representation in Figure 3 depicts the annual publication [26] counts from 2014 to 2023 in mental disorders.

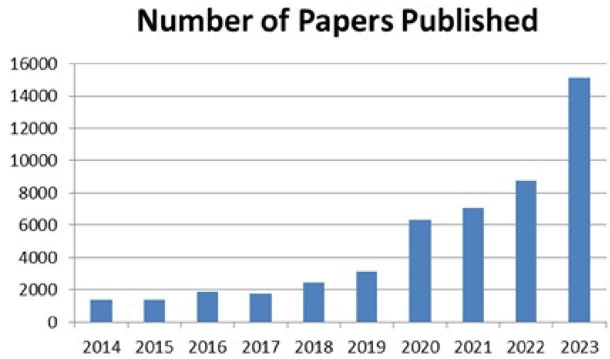

Fig. 3: Survey of Mental Health Disorder Research between 2014 to 2023 [26].

Yun et al [27] employed DNN and ML classifiers to analyze 19,725 participants in the NHANES. They found that ML classifiers trained on NHANES data were effective in predicting depression in K-NHANES. Among the classifiers tested, logistic regression demonstrated the better performance, closely followed by the DL algorithm. These findings highlighted the potential of ML and DL approaches for improving depression prediction and understanding the complex relationships between depression and various health and demographic variables.
Ghosh et al [28] conducted a study focusing on predicting depressed users and estimating the extent of their sadness by examining Twitter's social media data. The authors framed the problem as a supervised learning task and aimed to provide timely detection and estimation of depression intensity using social media content. They created a self-supervised renaming approach to improve the depression dataset and created a set of distinguishing characteristics unique to depression-related behaviour among users. The authors also suggested an LSTM network to identify depressed users on Twitter at various intensities. These findings highlighted the potential of leveraging social media data and ML techniques for the timely identification and assessment of depression in online users.
Baek et al [29] introduced the Context-DNN model, which leveraged multiple regression for predicting depression risk. The model was designed by incorporating context information that influences depression and combining it with deep neural networks (DNNs). Through four performance evaluations, the proposed Context-DNN model demonstrated the capability to accurately assess one's context in relation to the risk of depression. This model offers the potential for ongoing mental health monitoring and preventive measures against depression. The researchers also planned to extend their work by developing a personalized health management model that classifies contexts based on individual situations, distinguishing between internal and external context information. Furthermore, they aimed to identify the external and internal factors that have an impact on each context, thus providing a more comprehensive understanding of the factors influencing depression risk. Yildirim et al [30] proposed a deep hybrid model that effectively merged the strengths of both LSTM and CNN architectures. By incorporating CNN layers to capture the temporal characteristics of the signals and utilizing LSTM layers for effective sequence learning, the deep model was engineered to leverage both aspects in detecting depression from EEG images. The authors utilized EEG images, allowing for a comprehensive analysis of the neural activity associated with depression. By leveraging the strengths of both CNN and LSTM architectures, the proposed deep hybrid model aimed to enhance the accuracy and effectiveness of depression detection based on EEG data.

2.3. Hybrid Approaches

Kaur et al [31] conducted a comparative analysis to evaluate the effectiveness of denoising physiological signals using different approaches. To provide mode selection criteria, the authors used detrended fluctuation analysis (DFA). The signals were denoised using DWT and WPT after being decomposed into individual components with VMD. The efficacy of the proposed technique was demonstrated through simulations conducted on both artificially contaminated and real depression databases.
Sharma et al [32] introduced a Hybrid method for depression screening using EEG data. The model demonstrated reduced computation complexity and time requirements by incorporating the windowing technique. The results indicated that the developed model achieved

high accuracy in detecting depression using EEG images while maintaining simplicity and practicality in its implementation. In their research, Saeedi et al. [33] investigated the use of brain connectivity methods, specifically GPDC and dDTF, in combination with several well-known DL algorithms. Their DL model successfully captured the characteristics of EEG images. The results demonstrated that this novel DL model effectively analyzed brain connectivity and outperformed previous studies in recent years. The technique holds promise for healthcare professionals in the early identification and intervention of patients with Major Depressive Disorder (MDD), aiding in timely support and treatment.

A cross-validation-based transfer learning (TL) method based on an already trained CNN was shown to be effective by Seneviratne et al. [34]. This method provided DL models with generalization and addressed the problem of a small number of training data. The researchers found that wavelet transform (WT) images derived from resting-state EEG data collected before treatment contained power spectrum patterns representing various frequency bands. These WT images demonstrated substantial capacities in treatment outcome prediction and successfully reflected the non-stationary nature of the EEG data. The findings highlight the potential of utilizing pre-treatment resting-state EEG data and TL techniques for developing robust DL models with enhanced generalization performance.

Shahabi et al. [35] approached the task of depression classification (DC) by formulating it as a severity level classification problem, aiming to achieve more nuanced classification outcomes. They utilized articulatory coordination features (ACFs) to capture the neuromotor coordination changes associated with psychomotor slowing, a characteristic feature of Major Depressive Disorder. Their study revealed that the segment-wise classifier's performance was enhanced when a session-wise classifier was trained on embeddings derived from it. These findings highlight the effectiveness of incorporating ACFs and leveraging RNN models for DC, with the session-wise classifier leveraging the strengths of the segment-wise classifier to improve classification accuracy.

Several patterns emerge across the reviewed material. Studies with questionnaire-based data [20-22] demonstrated the viability of employing machine learning models to diagnose depression, although they were frequently hampered by subjectivity and self-report bias. Approaches based on speech and social media data [24,28] provided novel possibilities for early screening, although generalizability across varied groups remained a difficulty. In contrast, techniques that used EEG images [23,25,30,31-34] presented objective neurophysiological markers of depression and emphasized the growing trend toward image-based or connectivity-based representations of EEG for deep learning.

When comparing methodologies, traditional ML models proved computationally efficient but often lacked the capacity to capture complex spatiotemporal patterns in EEG data. Deep learning approaches, particularly CNNs and LSTMs, demonstrated stronger performance by automatically extracting discriminative features, though at the cost of larger data requirements and computational demand. Hybrid and transfer learning strategies [31–35] emerged as promising solutions, combining the strengths of multiple paradigms to improve generalization on limited datasets.

Overall, the literature shows a transition from simple ML models to advanced DL and hybrid frameworks, with an increasing emphasis on EEG-derived images. However, few studies have critically examined the use of advanced CNN variants like ResNet50V2 for depression classification using EEG images. This inspires the current study, which uses ResNet50V2 to bridge this gap and improve classification performance.

3. Materials and Methods

A thorough explanation of the dataset, model architecture, and training optimization was provided to establish a strong basis for examining the accuracy of the DC system. The dataset for DC using the EEG image [36] served as a valuable resource for understanding the relationship between brain activity patterns and depression. By leveraging pretrained models that had been trained on extensive datasets like ImageNet [37], the training process on the dataset gained significant advantages in boosting the model's proficiency in accurately classifying the data. Once the dataset was collected, it underwent meticulous preprocessing and augmentation that enhanced its quality, diversity, and ability to generalize, ensuring optimal performance during subsequent analysis and model training stages. Transfer Learning was performed to optimize the training process, using features extracted from the ImageNet Dataset.

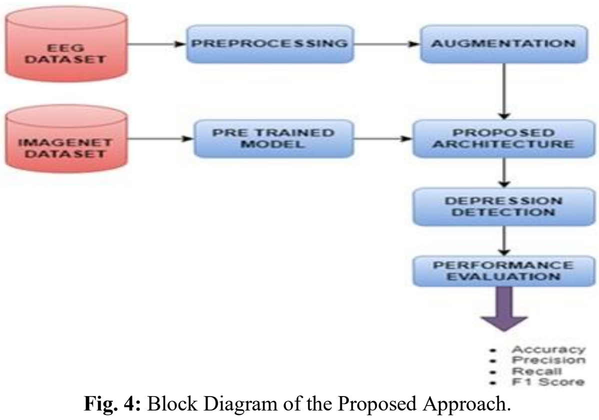

Fig. 4: Block Diagram of the Proposed Approach.

The evaluation process heavily relied on the proposed architecture as an integral element, leveraging its essential features and capabilities to perform the classification. For this study, the ResNet50V2 CNN model was selected as the preferred architecture, serving as the foundation for the proposed approach.

3.1. Dataset Description

The dataset for DC using EEG data is a valuable resource for understanding the relationship between brain activity patterns and depression. The images are stored in the EEG dataset accessible at https://figshare.com/articles/dataset/EEG_Data_New/4244171. The dataset comprised 724 EEG-derived images (380 from MDD patients, 344 from healthy controls), generated from 64 unique subjects—34 diagnosed with Major Depressive Disorder (MDD) and 30 healthy individuals. To avoid data leakage, we performed the train/test split on a subject-wise basis, ensuring that all images from any individual subject appear exclusively in either the training or test subset. Figure 5 presents EEG images from healthy individuals alongside those from patients with major depressive disorder in the dataset.

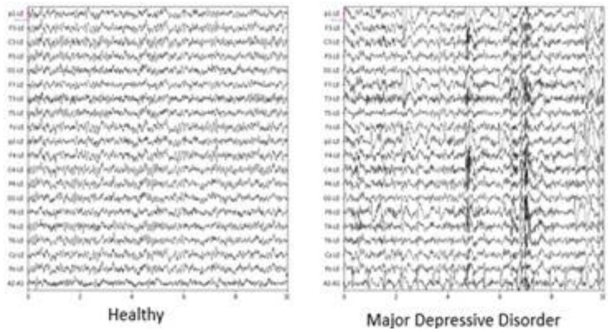

Fig. 5: Sample Images from the Dataset for Healthy and MDD Tuples.

Patients were selected in accordance with the experimental methodology authorized by the Human Ethics Council of Hospital University Sains Malaysia to create the dataset. The data collection process involved recruiting participants from different age groups, genders, and diverse backgrounds to ensure representation and generalizability of the findings. Consent forms were provided to participants, who were informed about the trial setup before signing. Before beginning the first EEG recording, the MDD patients underwent a two-week wash-out period to eliminate potential pharmaceutical side effects.

The visual representation of the classification of healthy and MDD patients in the dataset is shown in Figure 6.

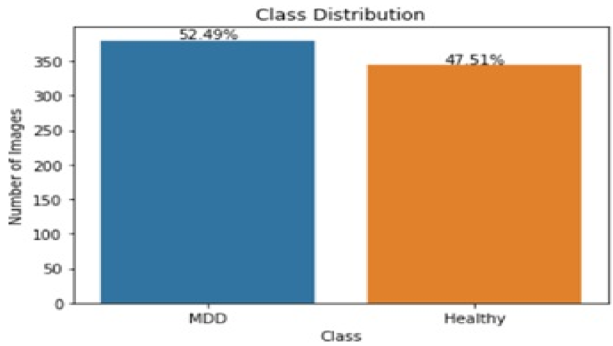

Fig. 6: Data Visualization.

This comprehensive dataset serves as a foundation for developing robust DL techniques for accurately classifying depression based on EEG data, enabling the development of effective diagnostic and treatment approaches. The description of the dataset split is demonstrated in Table 1.

Table 1: Description of the Dataset

Parameters	Count
Total images	724
Images for training	615 (85%)
Images for Testing	109 (15%)
MDD	380
Healthy	344

3.2. Pre-Processing and Augmentation

Data preprocessing and augmentation played crucial roles in preparing the dataset for training and enhancing the model's performance. The data preprocessing and augmentation methods explained in Table 2 increased the diversity of training images by introducing variations in orientation, position, brightness, and geometry, which helped the model generalize better, reduce overfitting, and improve its robustness to real-world variations in input data.

Table 2: Image Pre-Processing and Augmentation Techniques with Parameter Settings

Method	Value	Description
Rotation Range	10	Images randomly rotated up to 10 Degrees clockwise or counterclockwise
Width Shift Range	0.1%	Images are horizontally shifted up to 10% of their total width
Height Shift Range	0.1%	Images are vertically shifted up to 10% of their total width
Shear Range	0.1%	Shear transformation tilts the image in a certain direction, distorting its shape
Brightness Range	0.3 to 100 %	The brightness of images can be randomly adjusted between 30 % and 100 %

3.3. CNN and TL Approaches

In this study, CNNs were employed due to their proven effectiveness in processing image data structured in a grid format. CNN architectures typically consist of convolutional layers for feature extraction, pooling layers for dimensionality reduction, and fully connected layers for classification. These interconnected layers enabled CNNs to autonomously learn hierarchical representations from the input data, capturing essential local features and spatial dependencies critical for accurate image analysis.

Additionally, transfer learning techniques were incorporated to leverage existing knowledge from pretrained models, especially beneficial when working with datasets containing limited labelled samples. In this approach, the initial layers of a pretrained model were retained to preserve previously acquired feature representations, while the final layers were modified or extended to align with the specific requirements of the target classification task. This strategy not only reduced the computational cost and training time but also enhanced model generalizability and performance by reusing and adapting the learned features from established large-scale models to the problem domain addressed in this study.

The detailed image classification process proposed in this research using CNN and TL is illustrated in Figure 7.

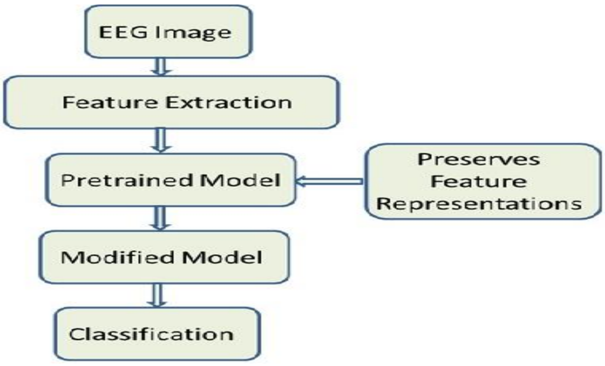

Fig. 7: Block Diagram Illustrating CNN and TL Workflow for Image Classification.

3.4. Proposed Architecture

ResNet50V2 was used as the base CNN model. ResNet50V2 was chosen as the backbone architecture due to its proven robustness in image classification tasks, where its residual connections effectively mitigated the vanishing gradient problem in deep networks. Compared with other architectures of ResNet variants such as VGG and EfficientNet, ResNet50V2 offered an optimal balance between computational efficiency and representational power, making it particularly suitable for learning discriminative features from EEG-derived imagery. Transfer learning was applied to optimize the training process. Transfer learning is performed using features extracted from the ImageNet Dataset. Figure 8 presents the architecture of the proposed methodology using ResNet50V2.

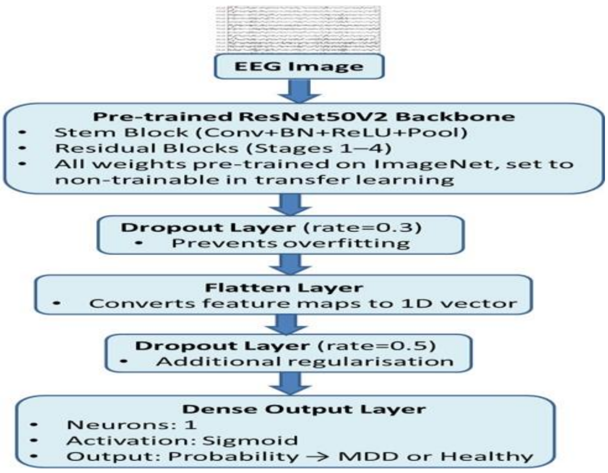

Fig. 8: Proposed Architecture Using ResNet50V2.

In the ResNet50V2 workflow, the input image was first passed through a series of initial convolutional layers. These layers employed filters to convolve over the input image, detecting and extracting low-level features. Activation functions, ReLU (Rectified Linear Unit), were applied after each convolutional operation to introduce non-linearity and enable the model to learn complex patterns. The distinguishing feature of ResNet50V2 was its use of residual blocks, each containing multiple convolutional layers designed to learn residual mappings. This was achieved by introducing skip (shortcut) connections, which allowed the model to learn the residual information between the input and output of the block. Additional convolutional and pooling layers further processed the outputs of the blocks, reducing the spatial dimensions of the feature maps while increasing the number of channels. Through this hierarchical processing, the model captured both local and global context from the input images. Finally, the extracted features were passed through fully connected layers and a softmax layer for classification, generating the final predictions. The hyperparameters used in the proposed research model are presented in Table 3.

Table 3: Hyperparameters Used in the Model

Parameters	Values
Optimizer	Adam
Activation Function	Sigmoid
Learning Rate	0.01
Loss	Binary Cross-Entropy
Batch Size	64
Number of epochs	20

The selection of hyperparameters in deep neural networks was a critical aspect that heavily impacted the learning process and overall effectiveness of the model. Parameters like learning rate, batch size, number of layers, activation functions, and regularization techniques were determined empirically to optimize the model's performance. Careful consideration of these hyperparameters was necessary to strike a balance and prevent problems such as overfitting, where the model memorized the training data, or underfitting, where the model failed to capture complex patterns in the data. The tuning of these hyperparameters required experimentation, analysis of training and validation performance, and an understanding of the specific task and dataset to ensure optimal model behavior and achieve the desired results. Figure 9 shows the proposed CNN model, and Table 4 depicts the proposed model summary.

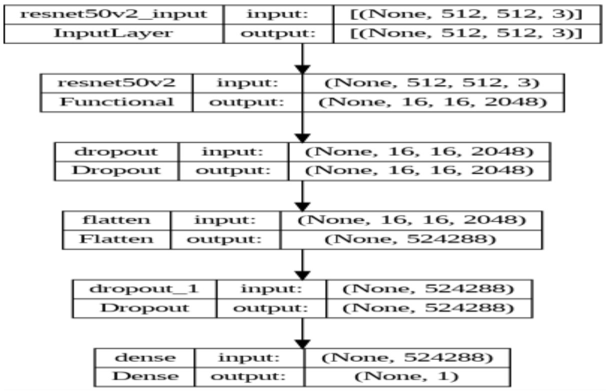

Fig. 9: The Proposed CNN Model.

Table 4: Proposed Model Summary

Layers	Type	Output shape	Parameters
Input layer	Functional	2048	23564800
Dropout layer	Dropout	2048	0
Flatten layer	Flatten	524288	0
Dropout layer	Dropout	524288	0
Fully connected layer	Dense	1	524289
Total Parameter			24,089,089
Trainable Parameter			524,289
Non-Trainable Parameter			23,564,800

4. Result and Analysis

4.1. Hardware and Software Setup

The study was conducted using the Google Colaboratory platform [38] along with the Microsoft Windows 10 operating system to provide a robust computational environment. The models were implemented in Python, employing the Keras package [39] with TensorFlow as the backend. The proposed models were designed to process the preprocessed and augmented dataset, thereby enabling accurate depression classification (DC). Model performance was evaluated by assessing predictions on the test dataset using the trained model.

4.2. Experimental Results

Table 5 presents the key performance metrics used to evaluate the proposed CNN model for depression image classification. The metrics include Accuracy, Precision, Recall, and F1-Score, along with their respective equations and obtained values.

Table 5: Performance Parameters

Parameters	Equation	Values in %
Accuracy	(TP+TN)/(TP+TN+FP+FN)	97.25
Precision	(TP)/(TP+FP)	95
Recall	(TP)/(TP+FN)	100
F1-Score	2*(Precision x Recall)/(Precision +Recall)	97.43
	TP=True Positive	
	TN=True Negative	
	FP=False Positive	
	FN=False Negative	

By analyzing these performance metrics, a comprehensive understanding of the model's classification capabilities was obtained, allowing us to ascertain its effectiveness in accurately classifying depression images in the dataset. The models were implemented and trained using Python and TensorFlow after the dataset was preprocessed and augmented. The Adam optimization algorithm was employed for prediction, and a batch size of 64 was used during the training of the CNN.

Figure 10 presents the plots of accuracy and loss for both training and validation datasets over the course of 20 epochs.

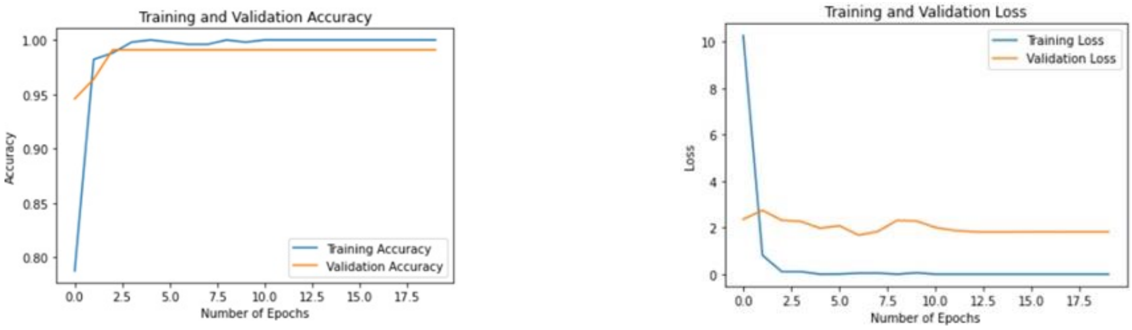

Fig. 10: Accuracy and Loss Plot.

Visualizing accuracy and loss plots throughout the training phase offered valuable information about the model's performance. The accuracy plot provided a visual representation of how the CNN performs in terms of correct predictions as the training epochs progress. It gives insights into the effectiveness of the CNN in classifying the data. Conversely, the loss plot demonstrated how the model's error decreases over time during training, indicating how well the CNN converged towards an optimal solution. These plots were valuable for researchers and practitioners to analyze the training dynamics of the CNN, detect any potential issues of overfitting or underfitting, and make well-informed decisions about adjusting or optimizing the model to enhance its overall performance. In the case of the proposed system, the accuracy plot and loss plot depicted that the model achieved an impressive accuracy of 97.25% on the dataset.

Figure 11 presents the classification report generated for the proposed system, detailing its performance across different classes.

```
Accuracy: 0.972477
Precision: 0.950000
Recall: 1.000000
F1 score: 0.974359
Cohens kappa: 0.944698
ROC AUC: 0.971154
[[49  3]
 [ 0 57]]
Specificity:  0.9423076923076923
              precision    recall  f1-score   support

           0       1.00      0.94      0.97        52
           1       0.95      1.00      0.97        57

    accuracy                           0.97       109
   macro avg       0.97      0.97      0.97       109
weighted avg       0.97      0.97      0.97       109
```

Fig. 11: Classification Report of the Proposed System.

The confusion matrix shown in Figure 12 served as an essential tool in assessing the performance of a DC system, as it offered a detailed overview of the model's predictions by comparing them to the actual labels, providing a comprehensive summary of its performance. By examining the matrix, the system's ability to correctly identify individuals with depression (true positives) and those without depression (true negatives), as well as misclassifications (false positives and false negatives), was assessed. This information helped in understanding the strengths and weaknesses of the classification system and guided further improvements to enhance its accuracy and reliability in identifying depression accurately.

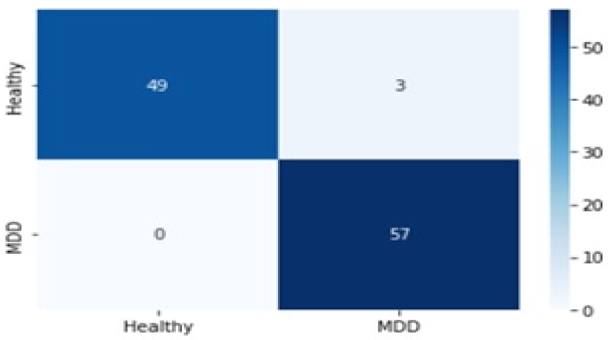

Fig. 12: Confusion Matrix of the Model.

Figure 13, which illustrated the trade-off between the true positive rate and the false positive rate at different classification thresholds, provided further insights into performance. The ROC curve, plotted from these values, depicted the balance between sensitivity and specificity

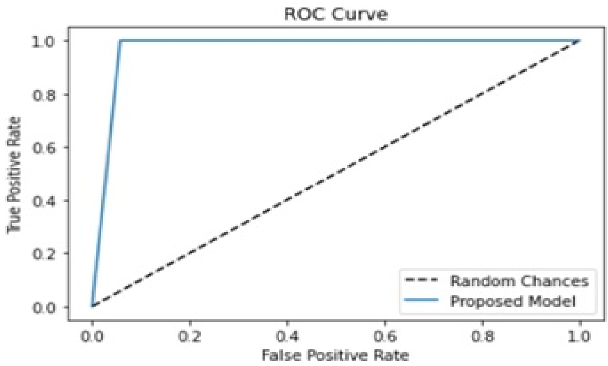

Fig. 13: ROC Curve of the Model.

The DC system exhibited excellent performance, as demonstrated by its high accuracy, sensitivity, and specificity. The system's ability to accurately identify individuals with depression and correctly classify those without depression showcased its effectiveness. Figure 14 displayed representative samples with their corresponding predicted labels for healthy individuals and patients with MDD. The robustness of the system was further demonstrated by its low false positive and false negative rates, which minimized the risk of misdiagnosis.

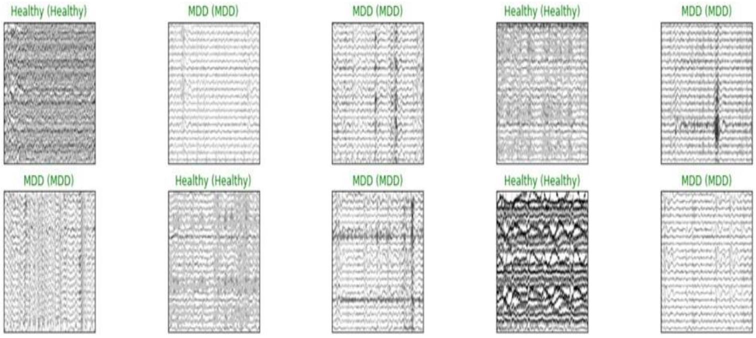

Fig. 14: Random Samples with Predicted Values.

Table 6 shows a comparison of the method proposed in this paper with other related studies on the same dataset. Overall, the existing research reported accuracies ranging from 88% to 95%. In contrast, the approach proposed in this paper achieved superior performance by leveraging ResNet50V2's deep residual architecture, which effectively overcame the vanishing gradient problem and enabled the learning of complex hierarchical features. The use of transfer learning with ResNet50V2 for EEG-based depression classification proved to be an effective strategy, especially in medical image analysis tasks where dataset size is limited and interpretability of subtle patterns is critical.

Table 6: Comparison of the Presented Methodology with the Art Method

Study	Methodology	Classification method	Accuracy
Yang, Jianli, et al. (2023) [40]	PSD + LZC + brain region combination (frontal, temporal, central)	SVM	92.4%
Mahato et al. (2024) [41]	Nonlinear features (SampEn, DFA) along with EEG band power features	SVM	95.23%
Yang, Jianli, et al. (2025) [42]	Fusion of LZC, SE, and KC features in the EO state and the PSD and SE features in the EC state	SVM	94.58%
Ahire (2025) [43]	Statistical Feature Extraction under three conditions: TASK, EC, EO	1DCNN	90.21%
Proposed	Transfer Learning+ ResNet50V2	ResNet50V2	97.24

5. Conclusion

The severity of depression in society is a significant concern with wide-ranging implications. Depression affects individuals of all ages, genders, and backgrounds, and its impact can extend beyond the individual to families, communities, and society as a whole. Emotionally, individuals continue to experience feelings of sadness, hopelessness, and a reduced sense of self-worth. Socially, they may struggle with maintaining relationships, isolating themselves, or feeling disconnected from others. Additionally, the physical effects of depression, such as fatigue, changes in appetite, and sleep disturbances, can persist even after the depressive episode. This article suggested a DL based method for DC. ResNet50V2 was used as the DL model, and transfer learning was applied to optimize the training process. The dataset comprised EEG images from both healthy individuals and patients diagnosed with Major Depressive Disorder (MDD) based on globally acknowledged diagnostic criteria for depression. The performance of the model was assessed using different performance metrics, resulting in an impressive accuracy rate of 97.25%. This DC system holds significant importance as it enables early identification and intervention for individuals at risk of or experiencing depression, leading to timely support and improved mental health outcomes. By accurately classifying depression, the system aids healthcare professionals in personalized treatment planning, optimizing resources, and reducing the burden on mental health services. Despite the promising results, translating this model into clinical practice poses challenges such as variability in real-world EEG recordings and potential artifacts that may affect performance. In addition, model interpretability remains essential for clinicians to trust and adopt AI-based tools in decision-making. To further strengthen clinical applicability, future work should include testing the model on larger and multi-center datasets to ensure generalizability across diverse populations. Another important direction is the integration of explainable AI methods, such as Grad-CAM, to visualize the EEG features most predictive of MDD, thereby enhancing trust and interpretability for clinicians and neuroscientists. Additionally, evaluating the model's ability to differentiate MDD from other psychiatric or neurological disorders with overlapping symptoms will be crucial for addressing comorbidity challenges in real-world clinical practice.

Conflict of interest

The authors declare that there is no conflict of interest.

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