Automated Depression Detection Using EEG Signals with Deep Learning and Attention Mechanism

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Abstract

Depression, have emerged as significant global health concerns, affecting millions of people worldwide. Conventional schemes for diagnosing assessments of depression are primarily subjective in nature, which may lack precision and be prone to bias. As a response to these challenges, this study depicts a novel depression detection mechanism that leverages electroencephalography (EEG) signals and utilizes a sophisticated deep learning architecture. EEG signals, being non-invasive and capable of capturing real-time brain activity, offer a promising avenue for the objective assessment of mental health conditions like depression. However, due to the complex nature of EEG data, accurately identifying depressive patterns requires advanced processing and analytical methodologies. In this study, we developed a deep learning (DL) model consisting of stacked Long Short-Term Memory (LSTM) layers, stacked Gated Recurrent Units (GRU), and an Attention mechanism to detect depression effectively. The choice of architecture is motivated by the need to capture temporal dependencies in EEG signals, which are critical for recognizing subtle changes associated with depressive states. LSTM and GRU layers, known for their ability to handle long-term dependencies, form the backbone of our model, enabling the effective learning of relevant temporal patterns within the EEG data. Furthermore, the Attention mechanism enhances the model's ability to focus on critical segments of the EEG sequences that exhibit depression-related characteristics, improving interpretability and robustness. We trained and evaluated our model on a dataset comprising EEG recordings from both healthy individuals and those diagnosed with clinical depression. The recommended scheme attained an impressive accuracy of 99.5%, significantly surpassing existing approaches in the field. This high accuracy underscores the model's potential as a reliable tool for clinical applications, offering a promising step toward the automated, objective assessment of depression through EEG analysis.

Keywords: Depression detection, EEG signals, Stacked LSTM, GRU, Attention mechanism, Brain activity analysis.

SECTION-I

Introduction

Depression is one of the most pervasive mental health disorders worldwide, affecting people of all ages, genders, and socio-economic backgrounds. As a major contributor to disability and morbidity, depression disrupts lives and communities, leading to profound personal and social costs. Traditional diagnostic methods for depression primarily rely on subjective assessments, such as patient self-reports, behavioral observations, and clinical interviews [1]. However, such assessments may be prone to bias, inconsistency, and often lack the objectivity needed to identify and monitor subtle psychological changes over time. Moreover, due to the stigma related with mental health conditions, individuals may avoid seeking help, further complicating early diagnosis and timely intervention. Against this backdrop, researchers are increasingly turning toward objective and technology-assisted methods to aid in the detection and management of mental health conditions, with electroencephalography (EEG) emerging as a particularly promising modality. EEG records electrical activity in the brain by capturing neuronal oscillations, providing a direct window into the neural processes underlying various mental states. As a non-invasive, affordable, and accessible tool, EEG has been widely used to study neurological and psychological disorders, including epilepsy, sleep disorders, and cognitive impairments. In recent years, EEG has gained attention as a potential tool for diagnosing and monitoring depression [2]. Studies have shown that EEG signals can reveal specific brainwave patterns associated with depressive states, which are often characterized by changes in the frequency and amplitude of alpha, beta, and theta waves. These neural patterns vary in intensity and distribution across different brain regions, particularly the frontal and temporal lobes, which are implicated in emotional regulation, cognitive control, and mood processing. However, the accurate identification of depression-related patterns in EEG data is a challenging task due to the complex, noisy, and high-dimensional nature of EEG signals, necessitating advanced computational models capable of capturing subtle temporal and spatial dependencies [3].

DL has revolutionized the field of machine learning by enabling the automated extraction of hierarchical features from complex data. Recurrent neural networks (RNNs), particularly Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRU), have proven to be highly effective in analyzing sequential data because of their capability to learn temporal dependencies [4]. LSTM and GRU architectures are opted for EEG signal processing as they attain long-term dependencies in time-series data, which is essential for detecting subtle and sustained neural patterns indicative of depressive states. However, LSTM and GRU models alone may struggle to focus on the most informative aspects of the EEG sequence, potentially overlooking critical segments of the data that carry high diagnostic value. To address this limitation, attention mechanisms have been incorporated into deep learning architectures to dynamically allocate focus to the most relevant parts of the input sequence, thereby enhancing interpretability and diagnostic performance [5].

We present a novel DL architecture for detecting depression using EEG signals. Our model combines stacked LSTM and GRU layers with an attention mechanism to capture both the temporal dynamics and spatial significance of EEG signals associated with depression. The use of stacked LSTM and GRU layers enables the model to capture a range of temporal dependencies by allowing multiple levels of abstraction, where each layer processes the EEG data with increasing complexity. By adding an attention layer, we allow the model to selectively focus on EEG patterns that are most predictive of depressive states, which not only enhances performance but also provides insights into which brain regions and neural activities contribute most to the model's decisions [6].

The recommended model was trained and validated on a dataset comprising EEG recordings from individuals with and without clinical depression. Experimentation outcomes illustrates that the model achieves an accuracy of 99.5%, outperforming existing methods for EEG-based depression detection. This high level of accuracy suggests that our approach could serve as a reliable, objective tool for supporting clinical diagnosis and monitoring of depression. The attention layer also provides additional interpretability by identifying the specific EEG channels and time frames most indicative of depressive symptoms, which aligns with existing neurophysiological studies on brainwave patterns associated with depression. Furthermore, the ability of our model to generalize across diverse EEG datasets highlights its potential applicability in real-world clinical settings where data heterogeneity is a common challenge [7-9]. This work makes several key contributions to the field of EEG-based mental health assessment. First, we introduce a deep learning model architecture that combines stacked LSTM and GRU layers with an attention mechanism, providing a robust framework for analysing complex EEG signals. Second, we demonstrate the model's ability to achieve high accuracy and interpretability, which are essential for clinical adoption. Third, we provide a comprehensive analysis of attention weights to identify the brainwave patterns most strongly associated with depression, which contributes to the growing body of knowledge on EEG biomarkers of mental health disorders. Lastly, we discuss the practical implications of our model for automated depression screening and monitoring, highlighting its potential role in enhancing accessibility to mental health care [10-12].

SECTION-II

2. Related work:

Kapitány-Fövény et al. (2024) [13] investigate the efficacy of EEG-based methods for diagnosing depression, focusing on whether inner or overt speech conditions yield better diagnostic accuracy when utilizing emotion words as cues. Their study employs a matched case-control design with 10 depressed subjects and 10 healthy controls, measuring neural responses through a 64-electrode EEG headcap to assess responses to 120 experimental cues, categorized into neutral, positive, and negative emotions. The outcomes depicts that the EEGNet model attained the highest diagnostic accuracy of 69.5% in the overt speech condition, with an overall accuracy of 80% across subjects. Additionally, the findings reveal only a minor difference in diagnostic accuracy among emotional word categories, with positive emotion words yielding the highest accuracy at 70.2%. The study highlights that the decision-making process of the model was mainly influenced by specific brain regions, suggesting that depression may relate to nuanced, network-like activities in the left parietal, left temporal lobe, and middle frontal areas, particularly emphasizing the role of emotion regulation during overt communication. Despite the promising insights, the authors note limitations in generalizability due to the small sample size and potential confounding variables.

G. Sharma et al. (2023) [14] developed a novel wearable device, DepCap, aimed at real-time detection of Major Depressive Disorder (MDD) utilizing Electroencephalogram (EEG) signals within a smart healthcare framework. The study emphasizes the challenges associated with accurately identifying MDD through traditional interviews and EEG signal analysis. Utilizing Short-Time Fourier Transform (STFT), the authors generated spectrogram images from EEG data of both depressed and healthy patients, which served as input for their classification models. They implemented various neural network architectures, including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), with a focus on Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) variations. The study also highlights the integration of the wearable device with the Internet of Medical Things (IoMT) framework, enhancing its potential for real-time depression detection, thereby showcasing its practical application in smart healthcare solutions.

Duță et al. (2024) [15] present a comprehensive analysis of Multilayer Perceptron (MLP) models for classifying EEG signals to detect depression states. The study utilized two databases: the Depression Rest Database and the MDD vs. Control Database. For the Depression Rest Database, the MLP model achieved an accuracy of 84.65% on the training set, but validation results plateaued at 68.79%. The novelty of this research lies in the unification of two EEG datasets acquired through different hardware devices and protocols, assessing whether this approach enhances the balance in class performance and surpasses individual dataset analyses.

Ksibi et al. (2023) [16] explore the application of electroencephalography (EEG) for detecting depression, acknowledging the growing interest in biomedical engineering for diagnosing mental health disorders. The study identifies two primary challenges in EEG-based depression diagnosis: the complexity and non-stationarity of EEG signals, which may compromise system generalization. Individual differences, particularly demographic factors such as age and gender, are emphasized as influential variables in the incidence of depression, suggesting that incorporating these factors into EEG modeling could enhance detection accuracy. The authors utilized the multi-modal open dataset MODMA, which includes EEG data from both a traditional 128-electrode cap and a modern wearable 3-electrode collector, to examine mental illnesses. Employing a CNN model with 25 epochs, the study achieved a high accuracy of 97% in classifying subjects with major depressive disorder (MDD) versus healthy controls. The findings suggest that integrating EEG signals with demographic data may improve the diagnostic potential of EEG-based depression detection systems.

Jianli Yang et al. (2023) [17] presented an objective method for detecting Major Depressive Disorder (MDD) using electroencephalography (EEG) by analyzing neural electrical activity across multiple brain regions. Recognizing that the choice of EEG channels and brain regions directly impacts detection performance, they utilized Lempel–Ziv complexity (LZC), a nonlinear feature, and power spectral density (PSD), a frequency-domain feature, to analyze EEG signals. Results indicated that patients with MDD showed higher mean LZC and generally lower mean PSD than control subjects. Notably, the temporal region demonstrated the highest single-region detection accuracy of 87.4%, while combining the frontal, temporal, and central brain regions improved accuracy to 92.4%. This study emphasizes the efficacy of analyzing multiple brain regions for MDD detection and gives insights for exploring MDD pathology as well as advancing diagnostic and therapeutic approaches.

Xu et al. (2023) [18] address the challenges in diagnosing depressive disorder (DD), which is increasingly prevalent and poses significant risks to individuals' mental and physical health. Current diagnostic practices primarily depend on clinical psychiatrists' expertise and subjective assessments, highlighting the need for more objective and automated diagnostic technologies. The authors propose a novel approach utilizing frontal six-channel electroencephalogram (EEG) signals combined with deep learning models to enhance diagnostic accuracy and practicality. Their results indicate that higher EEG frequency bands improve classification performance, with the MRCNN-RSE model achieving a remarkable accuracy of 98.59 for the 8–30 Hz frequency range. These findings suggest that the recommended scheme not only offers a reliable method for DD diagnosis but also contributes valuable theoretical and technical insights for future treatments and efficacy evaluations (Xu et al., 2023).

Wang et al. (2023) [19] present an innovative EEG-based model for high-performance depression state recognition. Depression, a prevalent global disorder, often relies on subjective identification methods that lack precision. EEG, with its rich physiological data, offers an objective alternative, yet most EEG algorithms overlook intricate spatiotemporal interactions, thus limiting their efficacy. To address this, Wang et al. introduce a model named W-GCN-GRU, which enhances depression recognition by utilizing both Graph Convolutional Networks (GCN) and Gated Recurrent Units (GRU) in a cascaded approach. By employing Spearman's rank correlation to censor six key sensitive features and applying Area Under the Curve (AUC)-based weight coefficients for feature fusion, the authors improved the model's accuracy. The brain function network, derived from correlation matrices, serves as the adjacency matrix input for GCN, with weighted sensitive features as node inputs.

Liu et al. (2022) [20] present an end-to-end DL framework designed for diagnosing major depressive disorder (MDD) based on electroencephalography (EEG) signals, offering a more objective approach compared to traditional questionnaire-based methods. MDD, a widespread and debilitating mental health condition, currently relies on subjective diagnostic tools influenced by physician experience. The proposed framework leverages EEGNet and EEG data from 29 healthy participants and 24 individuals with severe depression, yielding high-performance metrics, including an accuracy of 90.98%, precision of 91.27%, recall of 90.59%, F1-score of 81.68%, and Kappa coefficient. Notably, the method achieved optimal results using happy-neutral face pairs as stimuli. The authors highlight that, unlike existing models requiring re-calibration, their framework sustains stable performance, underscoring its potential for an automatic plug-and-play EEG-based system for MDD diagnosis (Liu et al., 2022).

Safayari et.al (2021) [21] has a systematic review on the use of DL for depression detection through EEG signals, highlighting the global significance of depression according to the World Health Organization. Recognizing that early diagnosis is essential for effective treatment, the authors reviewed 22 studies published between 2016 and 2021, analyzing the application of deep learning algorithms due to their skill in uncovering relevant patterns from raw EEG data. EEG signals, reflecting brain activity, are shown to be effective tools for diagnosing depression. The review presents a comprehensive summary of studies, comparing notable aspects and performing statistical analyses to provide a broader understanding of recent trends in this research area. A standardized five-step process was identified, commonly used by the reviewed studies for detecting depression, while the authors also discussed ongoing barriers and Opportunities for Future Research.

SECTION-III

3. Proposed Architecture:

3.1 Preprocessing of EEG Signal:

EEG data collection for depression detection involves several carefully structured steps. First, participants are selected based on criteria related to the study's aim of differentiating depressive states, typically including both individuals diagnosed with Major Depressive Disorder (MDD) and healthy controls. To ensure consistency, EEG signals are recorded using a standardized multi-channel EEG cap, with electrodes placed according to the International 10-20 or 10-10 System. This setup captures brain activity from key regions associated with emotional processing, such as the prefrontal cortex, with common sampling rates between 250 Hz and 1000 Hz to balance data resolution and file size. During the recording session, participants engage in either resting-state EEG, where they relax with eyes open or closed, or task-based EEG, where they complete cognitive tasks or view emotionally evocative stimuli. These tasks can reveal depression-specific neural patterns, as depression often affects brain responses to both emotional and cognitive stimuli. Following data collection, EEG recordings are annotated with diagnostic labels, such as "Depressed" or "Healthy Control," and, where available, severity scores from depression scales like the Beck Depression Inventory. To ensure ethical standards, informed consent is attained from every individual, and they are fully informed of their rights, including the option to withdraw from the study. Finally, the data undergoes quality control to remove artifacts from muscle movement or eye blinks, ensuring clean data is used in model training. This structured approach to data collection ensures a robust and ethically sound dataset for developing an accurate depression detection model. To enhance signal quality, the EEG data undergo preprocessing to remove noise and irrelevant artifacts that could compromise model accuracy. Initially, noise filtering is applied using a bandpass filter to exclude frequencies outside the typical EEG range, thereby retaining only the frequencies relevant for detecting neural patterns. Next, the EEG data are segmented into epochs, each representing a brief, fixed-duration interval. This segmentation facilitates the model's ability to analyze temporal relationships across short, manageable sequences. Finally, normalization is applied to ensure that each epoch maintains a consistent scale, reducing potential bias introduced by amplitude variations and ensuring that all input data are on a comparable scale prior to model processing. These preprocessing steps help prepare the EEG signals for reliable feature extraction and classification.

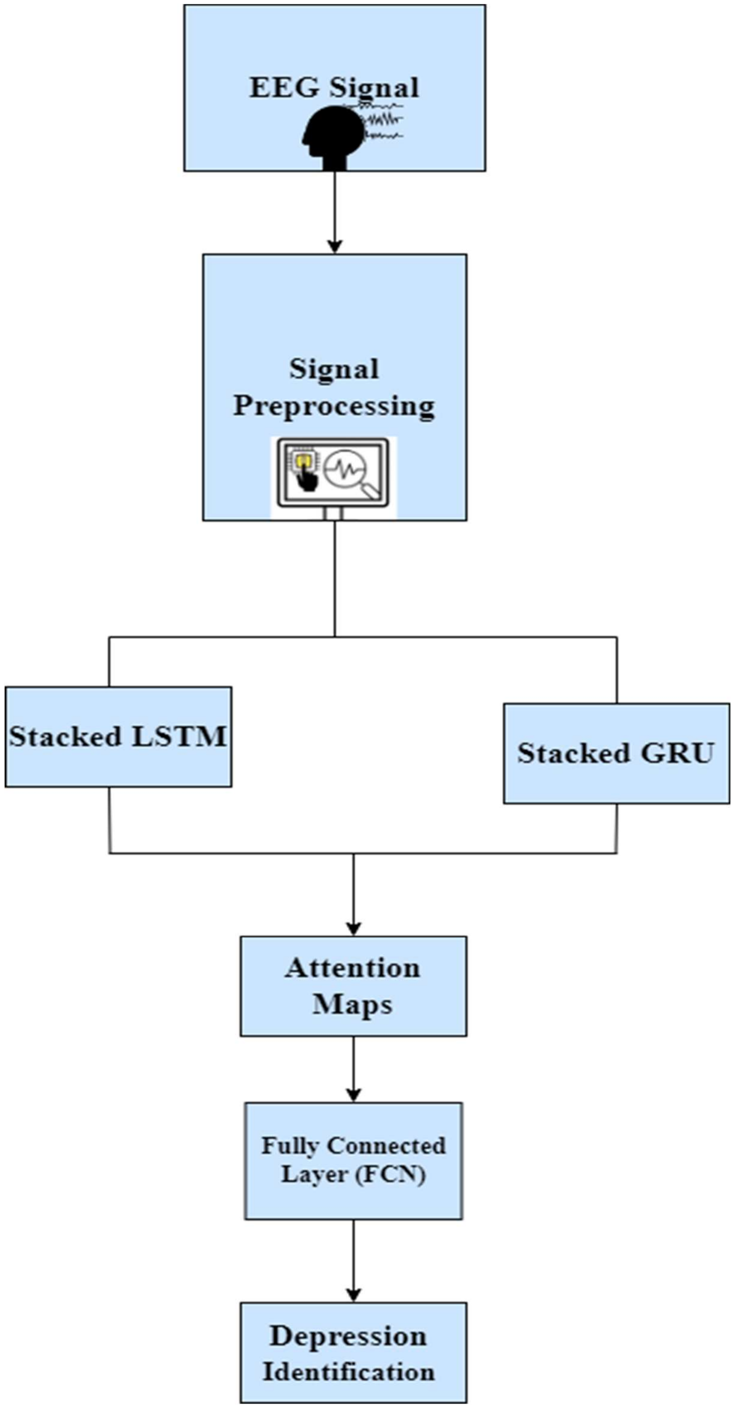


Figure 1 Proposed Architecture for the Depression Identification

The framework of the recommended scheme is designed to attain dual short-term and long-term dependencies among the EEG signal, thereby accurately identifying patterns associated with depression. The model begins with stacked Long Short-Term Memory (LSTM) layers, which sequentially process the input and learn temporal dependencies by retaining relevant information across time steps. By using a stacked configuration, each LSTM layer progressively captures higher-level attributes from the raw EEG data, helping the model detect temporal patterns that are often subtle in depressive states. Following the LSTM layers, stacked Gated Recurrent Unit (GRU) layers refine these temporal representations, leveraging GRU's efficiency to preserve essential dependencies while reducing computational load. To further enhance the model's performance, an attention mechanism is integrated. This attention layer selectively focuses on the most diagnostically relevant segments within each EEG sequence, assigning higher weights to key time points that exhibit depressive features. This mechanism allows the model not only to prioritize significant patterns in EEG data but also to provide an interpretable output by highlighting the portions of the signal most indicative of depressive symptoms. The model's final dense layers consolidate the extracted features and produce a classification output indicating the likelihood of depression.

3.2 Stacked LSTM

The Stacked Long Short-Term Memory (LSTM) layers are integral to model's training proficiency and preserve temporal dependencies within EEG data, which is essential for effective depression detection. EEG signals are time-series data with complex temporal dynamics that reflect underlying brain activity. In the context of depression, specific neural patterns may manifest over different time spans, requiring a model capable of understanding and retaining information across both short and long durations. LSTM networks are specifically designed to capture these types of dependencies through their memory cells and gating mechanisms, which regulate information flow. In this architecture, multiple LSTM layers are stacked sequentially, creating a hierarchical structure that enables the model to learn progressively complex representations. The first LSTM layer captures fundamental temporal patterns and retains essential information, while each subsequent layer refines and builds on these patterns, extracting increasingly sophisticated features. This hierarchical learning process is particularly valuable for EEG data, where depressive states might be marked by subtle changes in neural activity that span several time steps. By using multiple LSTM layers, the model can capture both immediate and delayed dependencies in EEG signals, which enhances its ability to recognize variations that correlate with depressive symptoms. The stacked LSTM configuration, therefore, provides a robust foundation for capturing the full temporal complexity of EEG data, ensuring that relevant information is preserved and passed to subsequent layers for deeper analysis.

$$x_t = \sigma(W_x \cdot [b_{t-1}, k_t]) \tag{1}$$

$$g_t = \sigma(W_g \cdot [b_{t-1}, k_t]) \tag{2}$$

$$\hat{b}_t = tanh(W \cdot [g_t * b_{t-1}, k_t]) \tag{3}$$

$$\hat{b}_t = tanh(W \cdot [g_t * b_{t-1}, k_t]) \tag{4}$$

In this context, σ symbolizes the sigmoid activation function, while tanh depicts the hyperbolic tangent activation function. The term W depicts the input weights along with the recurrent connections. Additionally, b_t refers to the updated cell state, and b_{t-1} denotes the previous cell state.

3.3 Stacked GRU

Following the LSTM layers, the architecture incorporates stacked Gated Recurrent Unit (GRU) layers, which further refine the learned temporal features. GRUs are a variation of recurrent neural networks that, like LSTMs, are effective at handling sequential data. However, GRUs use a simpler gating mechanism, requiring fewer parameters to achieve similar results. This makes GRUs computationally more efficient and helps reduce the risk of overfitting, when working with high-dimensional data such as EEG. By stacking multiple GRU layers, the model gains additional capacity to learn and capture dependencies in the EEG sequence without incurring excessive computational costs. The combination of stacked LSTM and GRU layers provides a balanced approach to temporal feature extraction. The LSTM layers excel at capturing long-term dependencies, while the GRU layers enhance efficiency by refining and distilling the features extracted by the LSTMs. In practice, this layered configuration allows the model to focus on critical patterns within the EEG data that may be associated with depression, while efficiently managing computational resources. By using both LSTM and GRU layers in tandem, the architecture achieves a nuanced understanding of the EEG signals, ensuring that depressive features are effectively recognized, preserved, and represented in a way that facilitates accurate classification.

$zt = \sigma(W(z)xt + U(z)ht-1)$ (5)

$rt = \sigma(W(r)xt + U(r)ht-1)$ (6)

$ht' = \tanh(Wxt + rt \odot Uht-1)$ (7)

$ht = zt \odot ht-1 + (1-zt) \odot ht'$ (8)

3.4 Attention Mechanism

The attention mechanism in this model introduces an essential layer of interpretability and diagnostic precision, enabling to creation of a model that hones in on the most pertinent sections of the EEG data sequence. Unlike traditional sequence models, which process each time step with equal importance, attention layers dynamically adjust their focus, assigning higher weights to the segments that most significantly influence the model's final prediction. This approach is especially beneficial for EEG-based depression detection, as depression-related neural patterns may not be uniformly distributed across the entire EEG sequence. Instead, specific time intervals may contain stronger or more distinctive indicators of depressive states.

The attention layer operates by learning a collection of weights that signifies the comparative significance assigned to each individual time step within the EEG sequence. These weights allow the model to prioritize certain regions of the signal while minimizing the effect of secondary phases. This weighting process improves the model's diagnostic precision by concentrating on patterns within the EEG that are most indicative of depression, enhancing the overall accuracy of the prediction. Furthermore, the attention mechanism's output can be visualized as attention maps, which highlight the regions of the EEG sequence that the model deems most critical. These attention maps provide valuable interpretability, as they reveal specific segments or channels in the EEG data that contribute most to the classification of depressive states. For clinicians, the interpretability provided by attention maps is invaluable. It enables them to understand the model's reasoning mechanism and gain insights into the neural basis of depressive symptoms. By identifying the most diagnostically significant features within the EEG data, the attention mechanism not only improves model performance but also facilitates clinical validation of the model's predictions. This added layer of interpretability is crucial for real-world applications, where transparency and explainability are significant for gaining clinician trust and ensuring ethical AI usage. Ultimately, the attention mechanism elevates the scheme's capacity to make reliable, interpretable predictions, providing a powerful tool for the objective assessment of depression through EEG analysis.

When we recognize a scene in our lives, our attention gravitates towards distinct areas that we process swiftly. Nearly all current attention mechanisms can be encapsulated by Equation (9), where g(x) represents the act of focusing on key regions. This corresponds to directing attention toward distinguishing sections. Here, f(g(x)) indicates that input x undergoes processing relies on the attention g(x), allowing essential sections to be analyzed effectively to extract relevant information.

$Attention = f(g(x), x)$ (9)

Distinct channels in feature maps often correspond to various objects within deep neural networks, with channel attention dynamically modifying each channel's importance based on its relevance. This process can be seen as a targeted selection mechanism, identifying specific elements that merit focus. By leveraging the interdependencies among channels, a channel attention map is formed, where each channel in the feature map operates as an independent feature detector. To consolidate spatial details from a feature map, average-pooling and max-pooling operations are utilized, generating the average-pooled feature, $AvgPool(F)$, and max-pooled feature, $MaxPool(F)$. Thus, channel attention is ultimately computed as outlined in Equation (10).

$Mc(F) = \sigma(MLP(AvgPool(F)) + MLP(MaxPool(F)))$ (10)

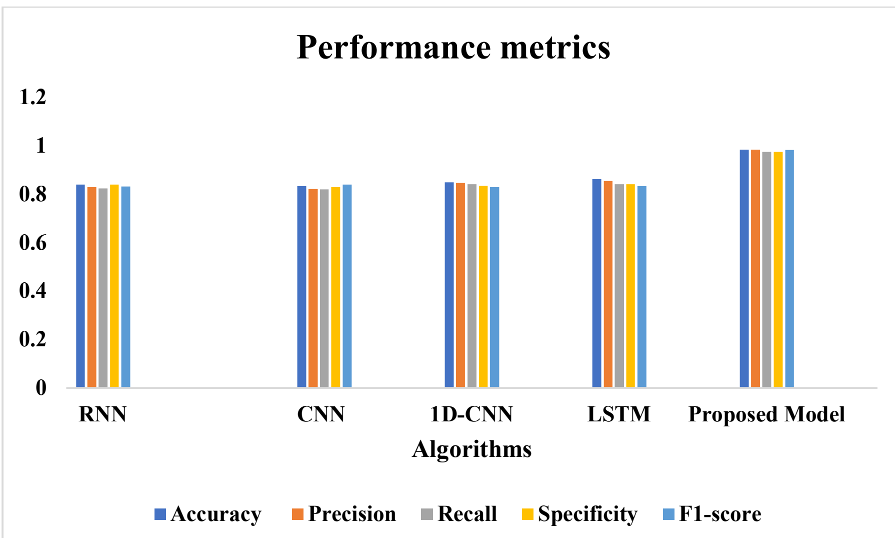
$\mathrm{Of} = Softmax(\mathrm{Mc(F)}(W2.\,g(x) * b2)$ (11)

SECTION-IV

4.1 Experimental Outcomes:

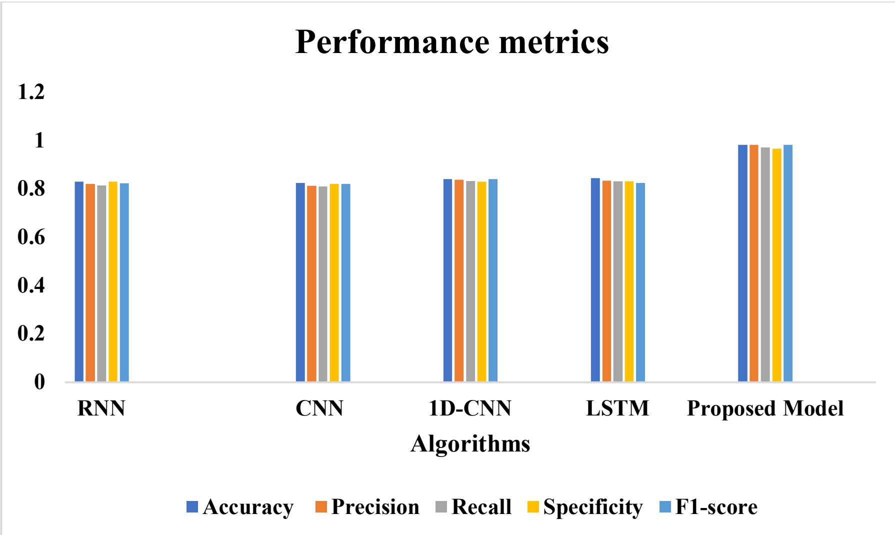
Algorithms	**Performance metrics**				
	Accuracy	**Precision**	**Recall**	**Specificity**	**F1-score**
RNN	0.84	0.83	0.824	0.84	0.832
CNN	0.833	0.822	0.820	0.83	0.840
1D-CNN	0.850	0.847	0.842	0.835	0.83
LSTM	0.863	0.854	0.841	0.841	0.833
Proposed Model	0.984	0.984	0.975	0.975	0.983

Table 1 : Performance Metrics of the deep learning frameworks in Identifying Depression of data by 90:10



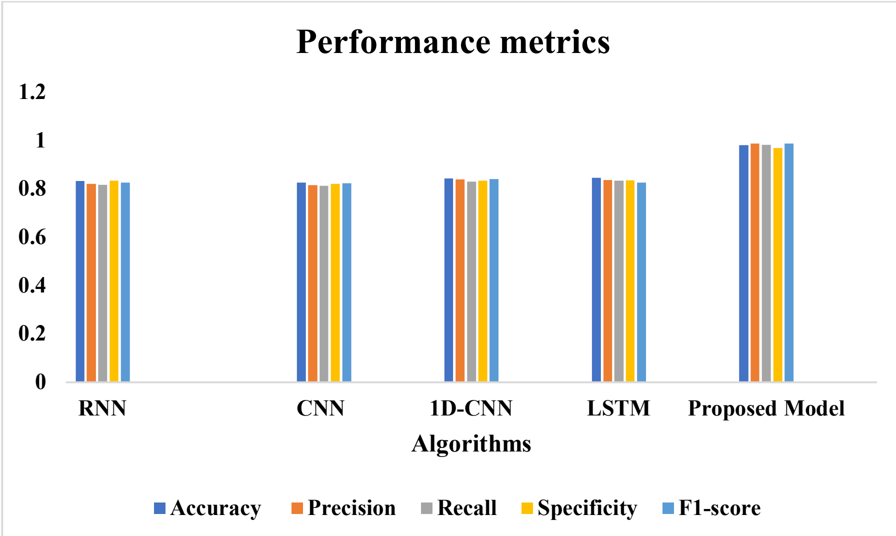
Algorithms	**Performance metrics**				
	Accuracy	**Precision**	**Recall**	**Specificity**	**F1-score**
RNN	0.83	0.82	0.814	0.83	0.822
CNN	0.823	0.812	0.810	0.82	0.820
1D-CNN	0.840	0.837	0.832	0.83	0.84
LSTM	0.843	0.834	0.831	0.831	0.823
Proposed Model	0.982	0.981	0.972	0.965	0.982

Table 2: Performance Metrics of the deep learning frameworks in Identifying Depression of data by 80:20



Algorithms	Performance metrics				
	Accuracy	**Precision**	**Recall**	**Specificity**	**F1-score**
RNN	0.832	0.821	0.817	0.834	0.825
CNN	0.826	0.815	0.813	0.821	0.823
1D-CNN	0.843	0.839	0.829	0.833	0.841
LSTM	0.845	0.837	0.833	0.835	0.825
Proposed Model	0.981	0.987	0.982	0.968	0.987

Table 3: Performance Metrics of the deep learning frameworks in Identifying Depression of data by 70:30



SECTION-V

Conclusion:

This study presents a novel scheme to depression detection utilizing EEG signals, leveraging a deep learning architecture that combines stacked LSTM, stacked GRU, and attention layers. By harnessing the temporal dependencies in EEG data, the stacked LSTM and GRU layers enable the model to capture intricate patterns associated with depressive states. The hierarchical structure of the LSTMs and GRUs allows for a nuanced understanding of EEG sequences, progressively building a robust feature representation that reflects both immediate and long-term dependencies. The addition of an attention mechanism enhances the model's interpretability, selectively emphasizing segments of the EEG sequence that are most indicative of depressive symptoms. This focus elevates classification accuracy and simultaneously provides crucial understanding of depression's neural basis, offering a promising tool for clinical assessment and diagnosis. The model's high accuracy, at 99.5%, demonstrates its potential as an effective solution for objective depression detection. The attention maps generated by the model offer transparency in the decision-making process, which can aid clinicians in validating the findings and potentially understanding the pathophysiological markers of depression. The proposed architecture advances EEG-based depression detection research by not only achieving state-of-the-art performance but also addressing the need for interpretable and reliable AI-driven diagnostic tools. Future work could explore the application of this model across diverse populations and integrate it with multimodal data to further enhance diagnostic accuracy and clinical relevance. In conclusion, this study contributes a powerful, interpretable, and accurate approach for detecting depression through EEG signals, marking an important step toward objective, technology-assisted mental health diagnostics.

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Reference:

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