EEGDepressionNet: A Novel Self Attention-Based Gated DenseNet With Hybrid Heuristic Adopted Mental Depression Detection Model Using EEG Signals

Mustufa Haider Abidi, Khaja Moiduddin, Rashid Ayub, Muneer Khan Mohammed, Achyut Shankar, and Stavros Shiaeles

***Abstract*—World Health Organization (WHO) has identified depression as a significant contributor to global disability, creating a complex thread in both public and private health. Electroencephalogram (EEG) can accurately reveal the working condition of the human brain, and it is considered an effective tool for analyzing depression. However, manual depression detection using EEG signals is time-consuming and tedious. To address this, fully automatic depression identification models have been designed using EEG signals to assist clinicians. In this study, we propose a novel automated deep learning-based depression detection system using EEG signals. The required EEG signals are gathered from publicly available databases, and three sets of features are extracted from the original EEG signal. Firstly, spectrogram images are generated from the original EEG signal, and 3-dimensional Convolutional Neural Networks (3D-CNN) are employed to extract deep features. Secondly, 1D-CNN is utilized to extract deep features from the collected EEG signal. Thirdly, spectral features are extracted from the collected EEG signal. Following feature extraction, optimal weights are fused with the three sets of features. The selection of optimal features is carried out using the developed Chaotic Owl Invasive Weed Search Optimization (COIWSO) algorithm. Subsequently, the fused features undergo analysis using the Self-Attention-based Gated Densenet (SA-GDensenet) for depression detection. The parameters within the detection network are optimized with the assistance of the same COIWSO. Finally, implementation results are analyzed in comparison to existing detection models. The experimentation findings of the developed model show 96% of accuracy. Throughout the empirical result, the findings of the developed model show better performance than traditional approaches.**

***Index Terms*—Depression analysis, mental depression detection, electroencephalogram, self-attention-based gated densenet, chaotic owl invasive weed search optimization, convolutional neural networks, spectral features.**

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I. Introduction

DEPRESSION is defined as a pervasive feeling of sadness and hopelessness that significantly impacts individuals in their day-to-day activities. Typically, depression may persist for up to two weeks, and if it endures for more than one week, it is diagnosed as Major Depressive Disorder (MDD) [1]. According to the World Health Organization (WHO), a staggering 322 million people worldwide are severely affected by depression, leading to substantial disability [2]. Individuals grappling with depression exhibit various symptoms, including guilt, sadness, hopelessness, loss of interest, energy, sleep disturbances, concentration issues, and disruptions to other basic routines [3]. Various factors contribute to the onset of depression, including physical disorders, unemployment, poverty, substance abuse, traumatic life events, and other life-related challenges [4]. The recent COVID-19 pandemic has also induced depression in many individuals, attributed to factors like quarantine, lockdowns, and social distancing measures [5]. In this context, depression poses unpredictable threats to human health, with the ultimate severity potentially leading to suicidal tendencies [6]. Recognizing these challenges in early identification and implementing effective treatment measures is crucial for saving lives [7]. The identification of depression can be done through the analysis of electroencephalogram (EEG) signals. These signals are characterized as intricate, non-linear structures that are non-invasive and non-stationary, reflecting the activities of the human brain and its functional status [8]. Detecting abnormalities with the naked eye is deemed more complex due to various limitations [9]. Depression primarily disrupts brain activity, and the EEG signal serves as a validation of the brain's electrical activity, relying on synaptic relationships. Researchers assert that EEG signals can effectively assess the level of depression in individuals. Visual observations conducted over the long-term EEG signal reveal notable contrasts between depressed individuals and those without depression, introducing complexity and the potential for human errors [10]. Consequently, a computer-based depression analysis model has been developed using deep learning techniques. These methods have demonstrated commendable performance rates compared to computer-aided techniques derived from intricate concepts [5], [11], [12]. These well-organized concepts play a pivotal role in shaping the layers of depression detection approaches. Additionally, the layer involving multiple processing plays a crucial role in data and pattern structure identification [13]. Moreover, multi-layer techniques find widespread application across various fields, including the automotive industry, agriculture, and the medical sector [14], [15], [16]. Most deep learning structures engage in automatic learning and extract features from raw input data [17]. The intricacies encountered in manually observing EEG signals are addressed effectively by employing deep learning models to effortlessly identify essential features [18]. This deep learning eliminates the need for a specifically crafted, hand-modeled classifier to resolve classification issues [19]. Therefore, the development of a novel automated MDD identification framework becomes imperative, leveraging deep learning approaches that help to solve the diverse complexities inherent in existing Major Depressive Disorder (MDD) detection models.

Various contributions associated with the developed automatic MDD identification framework are outlined below:

- Introducing a novel MDD recognition model that employs deep learning techniques and meta-heuristic approaches to identify depression in individuals at the initial stages.
- Executing optimal weighted feature fusion through the utilization of recommended COIWSO, which determines optimal features and optimized weights. This process aims to achieve optimal weighted fused features, thereby maximizing the correlation coefficient between the features.
- Implementing an effective depression detection framework called SA-GDensenet. This framework incorporates the developed COIWSO for parameter optimization to enhance accuracy and efficacy rates compared to conventional techniques.
- A hybrid heuristic scheme named COIWSO will be created for tuning weights and features during the optimal weighted feature fusion phase. Additionally, optimizing the optimizer and activation function in Gated DenseNet is carried out to improve the overall performance of depression identification.
- Conducting a performance analysis of the proposed depression detection framework through multiple analyses involving different classifiers and heuristic techniques. The objective is to demonstrate an improved depression identification rate compared to traditional techniques.

In Section II, various research works on existing depression detection frameworks are discussed. Section III delves into the explanation of the developed EEG-based depression detection framework and deep learning models. Section IV introduces optimal weighted feature fusion for depression analysis. The presentation of the Self-attention-based Gated DenseNet for depression detection can be found in Section V. Section VI covers different analyses and observations conducted for the developed depression detection model, while the conclusion is presented in Section VII.

II. Literature Review

This section presents the existing literature within the field of machine learning applications for EEG.

A. Related Works

Seal et al. [20] proposed an innovative framework, the Deep Network (DeprNet), which utilizes EEG signals for identifying depression. Fu et al. [21] introduced the Symmetric Convolutional and Adversarial Neural Network (SDCAN) to categorize depression using EEG signals. Hamid et al. [22] suggested a fused model for depression classification, incorporating facial and EEG features. The Bidirectional Long Short-Term Memory (BiLSTM) deep structured model, initiated with a feature fusion basis of facial and EEG data, outperformed other models in state-of-the-art analysis. Baek et al. [23] initiated a depression prediction model with a DNN and a multiple-regression approach. Sharma et al. [24] developed a neural network framework for analyzing depression using EEG signals. Akbair et al. [25] proposed a novel depression identification approach involving Reconstructed Phase Space (RPS) and EEG signals. Malviya et al. [26] suggested a depression recognition framework named Discrete Wavelet Transform (DWT), employing hybrid approaches like BiLSTM and CNN to detect individual stress levels. Souza et al. [27] proposed a DAC Stacking framework to identify anxiety and depression among individuals using standard datasets. Srinivasan et al. [38] have implemented the Deep CNN model for detecting the disease at an early stage with the help of three classification tasks. Here, the deep CNN model has outperformed the efficient performance when compared with other existing approaches. Sangeetha et al. [39] have developed the Multimodal Fusion Deep Neural Network (MFDNN) model to provide better diagnostic accuracy for different modalities in the medical field. However, a different analysis was performed for the validation to offer better performance for the developed model. Thus, the developed MFDNN model has shown reliable performance in degrading the misclassification error while treating the disorder.

B. Problem Statement

Early recognition of illness holds significant importance for effective treatment. A deep learning algorithm is highly efficient in discovering patterns and learning features with high accuracy. Previous works on depression detection, as shown in Table I, include DeprNet [20], which boasts high performance in

TABLE I
REVIEW ON DEEP STRUCTURE-BASED DEPRESSION DETECTION TECHNIQUES

Author [citation]	Approaches	Advantages	Challenges
Seal et al. [20]	DeprNet	• It provides high performance in terms of speed. • It obtains high precision, sensitivity, and specificity.	• It does not consider the redundancy features. • This leads to avoiding significant features during feature extraction.
Fu et al. [21]	SDCAN	• It detects stress levels at high speed. • The false acceptance rate is very low.	• It requires a large amount of data for detection. • It requires a high cost for implementation.
Hamid et al. [22]	BiLSTM	• It has high scalability and availability. • It is much faster than LSTM models.	• It does not fit for recognition. • It is very costly, and it is hard to train the data.
Baek et al. [23]	DNN	• It is used to predict the potential context that influences the risk of depression; hence, the detection performance is higher. • It identifies the local variations independently.	• It leads to overfitting. • It has a low ability to extract patterns from the raw data.
Sharma et al. [24]	DepHNN	• The implementation of the detected model is very easy. • It takes less computation complexity and provides high accuracy.	• It takes more time to train the classifier. • It is difficult to train complex data.
Akbari et al. [25]	SVM, RBF, KNN	• Easy to identify the linear decision boundaries. • It is highly possible to process large datasets and non-linear data as well, achieving good approximate complex functions by solving the insufficient diagnostic capability problem.	• It requires high memory. • It has low effectiveness and low generalization ability.
Malviya et al. [26]	DWT, CNN-BLSTM	• It is used to increase the low-resolution image components to high. • It provides a high compression ratio.	• It needs a lack of phase transformation that leads to misdiagnosing the disease. • It leads to poor directionality.
Souza et al. [7]	Ensemble deep learning	• It provides a promising objective approach. • It can extract relevant features.	• It does not encode the position of the object. • It needs lots of training data.

terms of speed, precision, sensitivity, and specificity. Despite its strengths, DeprNet overlooks redundancy features, potentially avoiding significant aspects during feature extraction. SDCAN quickly detects stress levels [21] with a very low false accept rate. However, it demands a substantial amount of data for detection and incurs high implementation costs. BiLSTM exhibits high scalability and availability [22] while being faster than LSTM models. Nevertheless, it is ill-suited for recognition, proving expensive and challenging to train.

DNN predicts potential contextual influences on the risk of depression, resulting in higher detection performance [23], [27]. It autonomously identifies local variations but is prone to overfitting and struggles to extract patterns from raw data. DepHNN makes model implementation straightforward [24], offering high accuracy with lower computation complexity. However, training the classifier takes more time, and handling complex data presents challenges. SVM, RBF, and KNN facilitate the easy identification of linear decision boundaries [25], providing high accuracy with reduced computation complexity. Yet, they demand high memory, exhibit low effectiveness, and possess limited generalization ability. DWT and CNN-BLSTM enhance low-resolution image components to high, boasting a high compression ratio [26]. Despite these advantages, they lack phase transformation, leading to potential misdiagnoses and poor directionality. Ensemble deep learning emerges as a promising objective approach for diagnosing mild depression [7], automatically detecting crucial features. However, it does not encode the object's position and requires extensive training data.

1) Motivation: Numerous techniques like machine learning and deep learning strategies are adapted to detect mental depression. For efficient analysis, the data needs to be collected from the standard datasets, but it needs to be validated with the larger samples. Certainly, it often shows the misclassification error in the larger set of samples. So, the better prediction is needed for the accurate performance. These challenges motivate the development of an efficient depression detection model using advanced deep learning techniques. Here, the developed model is validated with the larger datasets to handle the misclassification issues. Moreover, the result analysis is validated with diverse performance analysis to show the existing algorithms.

III. EEG-Based Depression Analysis Using an Advanced Model of Deep Learning With a Soft Computing Framework

A. EEG Datasets Used for Depression Analysis

EEG signals are sourced from the Depression-Rest Dataset [28], encompassing approximately 122 subjects with EEG signals. The dataset exclusively comprises pre-processed files for analysis. Moreover, data bias occurs when there is limited information in the datasets which shows an inaccurate representation. Here, a total of 122 subjects are taken in this analysis, which seems to be considered less information in this dataset.

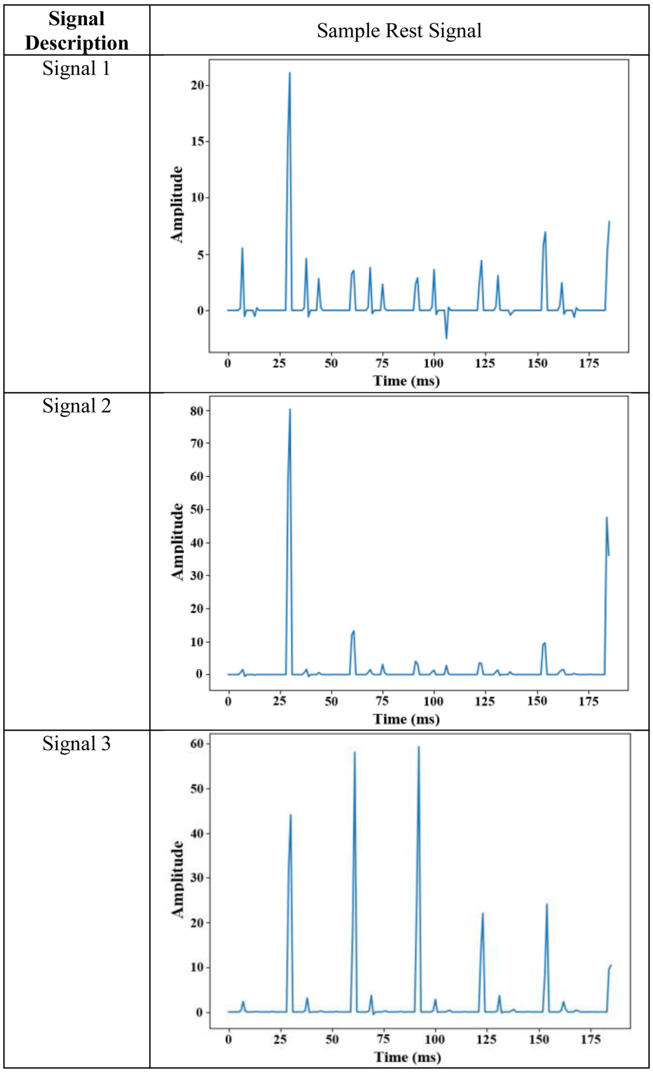

Fig. 1. Sample EEG signals from the considered dataset.

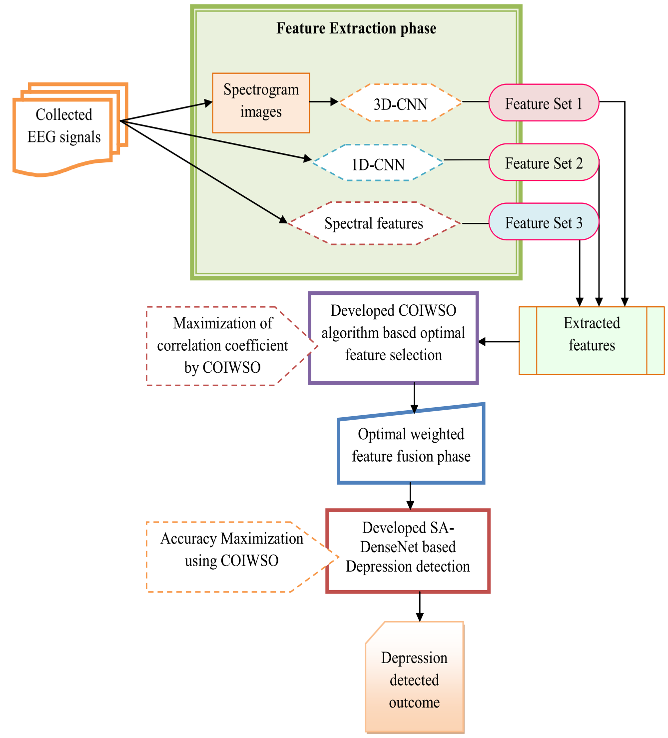

Fig. 2. Architecture of the recommended depression detection model.

Henceforth, the developed SA-GDenseNet model is performed to classify mental depression efficiently. Thus, it shows better impact on the result analysis in terms of accuracy maximization with the help of efficient tuning process by the designed COIWSO algorithm. Fig. 1 exhibits several sample signals extracted from the dataset. Here, the acquired EEG signals from the dataset are termed as SIG_h^{inp}, where $h = 1, 2, \ldots\ldots, H$, and H denote the total number of EEG signals for model analysis.

B. Proposed Depression Analysis

Depression, a persistent mental health condition, can disrupt daily routines for extended periods—years, months, or weeks. Addressing the complexities inherent in current approaches, there's an assured need for a novel framework to identify depression. The mental depression generally occurs through feelings or thoughts so; it is necessary to diagnose the mental disorder using EEG signals. Here, the EEG signal is used to record the electrical signals, which tend to diagnose depression based on the working status of the brain. That's why we have used EEG signals in this research area. Generally, the EEG offers better data privacy in terms of user identity, emotions, and so on. Moreover, informed consent is a procedure in which the healthcare provider informs the patient about the risk. But, the research work is concentrated on detecting mental depression using the developed model. Fig. 2 illustrates the systematic layout of the proposed Major Depressive Disorder (MDD) framework. The process begins with obtaining EEG signals from a benchmark dataset, serving as input to the feature extraction segment. This step yields three sets of extracted features. The first set results from converting EEG signals into spectrogram images, used as input for 3D-CNN, producing the initial set of features. The second set of features is acquired by inputting EEG signals into 1D-CNN. Subsequently, spectral features obtained directly from the original EEG signals constitute the third set.

In the optimal weighted feature fusion stage, a meticulous feature selection process is executed across the three sets—3D-CNN, 1D-CNN, and spectral features. Ten optimal features from each set are computed using the developed COIWSO. These optimal features are then introduced into the feature fusion stage, where the COIWSO-derived optimal weights maximize the correlation coefficient in the fused features.

The resulting optimal weighted fused features undergo a deep learning-based depression detection phase. The employed SA-GDensenet is designed to classify depression. The parameters, such as the optimizer and activation function, are optimized by the COIWSO to enhance the depression detection accuracy rate within the proposed depression identification framework.

C. Proposed Depression Analysis

The diverse machine learning approaches have seemed to be adapted for the efficient optimization process. However, there is a significant need to improve the models. Due to the complex parameters, the existing optimization algorithms are not efficient to attain a higher performance rate. In order to solve this issue, the COS and IWO algorithms are considered for their significant performance. Here, the COS ensures a balance between the exploitation and exploration phases [19]. However, it doesn't address discrete-time variant-based issues. To address these concerns, an alternative model, IWO, is integrated with the COS algorithm to create the COIWSO algorithm. IWO accurately identifies minima and effectively resolves premature convergence issues [29]. However, it lacks computational complexity, which degrades the system's performance. A novel depression detection model utilizes the suggested COIWSO to enhance the detection rate by optimizing parameters such as the optimizer and activation function in Gated DenseNet, along with the weights in optimal features. In the proposed COIWSO algorithm, the ultimate update occurs when satisfying the condition, *D*< 0.5. Should *D* be less than 0.5, the final update follows the COS approach; otherwise, the update is carried out following IWO. In this context, *D* represents a random number, a newly introduced parameter provided by the computation in (1).

$$D = \frac{BF - CF}{WF - CF} \tag{1}$$

In the provided parameter equation for determining fitness levels, the terms are designated as follows: *BF* represents the best fitness, *CF* denotes current fitness, and *WF* stands for the worst fitness. COS algorithm [19] is based on the hunting traits of barn owls that are known for its adept hearing in nocturnal prey detection. At the algorithm's inception, the primary task involves establishing the initial positions of owls. The population consists of m owls, each represented in the dimensional vector D as outlined in (2).

$$Q_s = (Q_{s1},\ Q_{s2},\ \ldots\ldots..,\ Q_{sD}) \tag{2}$$

The position of the sth owl in wth dimension is referred to as Q_{sw}. In a forest, to assign the initial position of every owl (3) is utilized.

$$Q_s = \ Q_N + rand\,(0,\ 1) * (Q_M -\ Q_N) \tag{3}$$

Here, the upper range is termed as Q_M and the lower range is referred to as Q_N and $rand(0, 1)$ the random number that is in the limit of [0, 1]. Next, the location of the owl is validated based on a fitness function *F*. Based on the fitness function, the intensity of information received by the owl's ear is computed. Moreover, the good owl Q_{Bst} is allocated to the owl which gains the enhanced intensity. Similarly, the bad owl is termed as Q_{Wst}.

$$ITN = \frac{F(Q_s) - Q_{Wst}}{Q_{Bst} - Q_{Wst}} \tag{4}$$

Here, the range of the best owl is given $Q_{Bst} = Max(\{F(Q_s))$ and also the worst owl is presented $Q_{Wst} = Min(\{F(Q_s) : s = 1, \ldots, m\})$ for the above equation. Every owl validates the distance information D_s to get the prey easily and it is provided in (5).

$$D_s = \ \|Q_s, X\|_2 \tag{5}$$

Here, the prey location found by the fitness owl is referred to as X, where $X = Q_{Bst}$. The modified intensity based on the inverse square law for sound intensity is provided in (6).

$$Jd_s = \frac{ITN_s}{D_s^2} + RN \tag{6}$$

Here, the term *RN* indicates random noise, which is utilized to offer a more realistic outcome. The new position allocation is given in (7).

$$Q_s^{v+1} = \begin{cases} Q_s^v + \beta * Jd_s * |\alpha U -\ Q_s^v|\, R_p & < 0.5 \\ Q_s^v - \beta * Jd_s * |\alpha U -\ Q_s^v|\, R_p & \geq 0.5 \end{cases} \tag{7}$$

The prey movement probability is termed as R_p a random number in which the limit [0, 0.5] is given α and also the constant utilized to minimize the linearity rate from the limit [1.9,0] in the iterations is offered as β that effectively allows better exploration in the search space.

IWO [29] is a nature-inspired optimization approach, and it also holds different phases to offer a better performance rate. The population initialization of weed in the D^{th} dimension is offered in (8).

$$Q = (Q_1,\ Q_2,\ \ldots,\ Q_D) \tag{8}$$

Here, the weeds position is given as *Q* that presents the trial solution of the optimization issue, which spreads over the D^{th} dimension issue with some random position. Every member of the population is allowed to generate a seed based on their abilities. The seed generated by the weeds improves linearly, starting from the smallest possible seed for the weed with the poorest fitness function up to the increased number of seeds in the plant with the optimal solution. Further, the produced seeds are distributed randomly in the D^{th} dimension search area with a generally offered random number and its mean is equal to zero. The non-linearity rate gets minimized rapidly which results in categorizing the fitter plants together and the unwanted plants are neglected. The random function of standard deviation σ effectively minimizes the iteration count from the pre-defined initial value σ_{Itl} and the final value σ_{Fnl} is validated in entire time steps by utilizing (9).

$$\sigma_{Itr} = \frac{(Itr_{Mx} - Itr)^a}{(Itr_{Mx})^a}\ (\sigma_{Itl} - \sigma_{Fnl}) +\ \sigma_{Fnl} \tag{9}$$

Here, the term Itr_{Mx} denotes the maximum iteration, σ_{Itr} is the standard deviation of the current time step, and finally, the non-linearity modulation index is presented as *a* in the above equation.

Based on rapid reproduction, the iteration numbers of reproduced plants in the colony reached the maximum, that is q_{Max}. In this process, the competitive model kicks in to eliminate undesired plants exhibiting poor fitness functions. It also allows the fitter plants to produce a greater number of seeds, which are accepted. This sequence is followed until the termination condition is met, and the plant with superior fitness is ultimately

Algorithm 1: Implemented COIWSO.

Initiate the population of COS and IWO
Allocate the parameters
For all the solutions
Validate the fitness function for an entire solution
Initialize the newly developed variable D
Renew the random variable
  If D<0.5
    Renew the final solution by COS
  Else
    Renew the final solution by IWO
  End If
End For
Return the optimal good solution

selected as the optimal solution. The pseudocode for the COIWSO optimization model developed is provided in Algorithm 1.

1) Algorithmic Description: Initially, the number of populations of existing COS and IWO algorithms is taken into account for the evaluation process. Then, the parameters are initiated, and the fitness function is evaluated for all the solutions in order to attain the optimal solution. However, the term D taken as the random variable and it also lies in the range of 0.5. Here, the iterative process is performed for validating the solutions optimally. If the random variable D is less than the value of 0.5 then, the solution gets updated in the existing COS algorithm; otherwise, the solution is updated in the IWO algorithm. In the end, the optimal solution is attained using the developed COIWSO algorithm.

IV. Depression Analysis Using EEG Signals by Extracting Three Sets of Features With Optimal Weighted Fused Features

A. Feature 1: Spectrogram With 3D-CNN Features

The acquired EGG signal SIG_h^{inp} is utilized to attain the spectrogram images. The spectrogram images undergo processing with a 3D-CNN to extract deep features. The 3D-CNN validates the image volume using a specified kernel set [30]. This structure comprises four convolution layers with associated kernel elements. Following this, a max-pooling layer is applied to each convolution layer, reducing spatial invariance and parameters. Subsequently, the ReLU activation function is utilized. The result obtained from the deepest convolutional layers is flattened and fed into the fully connected layer, serving as the classifier and presenting the extracted features from the convolutional layer. The attained feature from 3D-CNN is termed as FE_h^{3D-CNN} and offered to optimal weighted feature fusion phase.

B. Feature 2: 1D-CNN Features

The acquired EEG signals SIG_h^{inp} from the standard resources are offered as the input to 1D-CNN to obtain the deep features. In 1D-CNN, time-series signals are employed as the input in the input layer [31].

Convolution layer: In this layer, the convolution operation takes place within a specific area of the input signal to produce corresponding one-dimensional feature maps. Various kernels are employed to extract diverse features from the input signal. Equation (10) represents the 1-D convolution layer.

$$y_b^a = p\left(\sum_{c=1}^{N} y_c^{a-1} * l_{cb}^a + u_b^a\right) \tag{10}$$

Here, the convolution kernels are indicated as l, kernel count is given as b, channel number presented in the input is offered as N, bias performed in the kernel is provided as u, convolution operator is termed as$*$, and the activation function is referred to as $p()$ in the above-mentioned equation.

Pooling layer: Average pooling process is utilized to analyze the entire feature mapping that validates the signals based on their size in the predefined pooling window. Moreover, the maximal pooling window procedures choose the maximal parameter within a certain limit as the outcome value. The acquired features from 1D-CNN are presented FE_l^{1D-CNN} and they are provided to the optimal weighted feature fusion phase.

C. Feature 3: Spectral Features

The obtained EEG signals SIG_h^{inp} from the standard resources are utilized to attain the spectral features. Here, the STFT method is employed to capture the features of EEG signals. STFT analyses the variations in the signal by observing its frequency components and referencing the intensity value of each component. The STFT is designed to perform localized observations within the signal, utilizing a constant time window and multiplication on the input signal. The mathematical representation of STFT is provided in (11).

$$stft\left(\omega,\ j,\ \gamma\right) = \int_{-\infty}^{\infty} p\left(d\right) b * \left(d - j\right) \exp\left(-i\omega j\right) md \tag{11}$$

The function of the window is offered as $b * (d - j)$, a conjugate of complexity is presented as$*$, and the analytical signal is provided as $p(j)$ in the above STFT equation. The major utilization of STFT is to process the signal based on time and frequency domain. The acquired spectral features are termed as FE_t^{stft} and they are further offered to the optimal weighted feature fusion phase.

D. Optimal Weighted Fused Features

The attained three sets of features from 3D-CNN FE_h^{3D-CNN}, 1D-CNN FE_l^{1D-CNN}, and spectral features FE_t^{stft} are utilized in the optimal feature selection with the help of developed COIWSO. Here, the attained optimal features from 3D-CNN, 1D-CNN, and spectral features are termed as OF_w^{3D-CNN}, OF_i^{1D-CNN} and OF_p^{stft}, correspondingly. Then, the acquired three sets of optimal features are subjected as the input to the optimal weighted feature fusion phase. Here, the optimal weighted feature fusion is performed based on (12).

$$\begin{aligned} FFu_g^{tn} &= Wg_1 * OF_w^{3D-CNN} + Wg_2 * OF_i^{1D-CNN} \\ &\quad + Wg_3 * OF_p^{stft} \end{aligned} \tag{12}$$

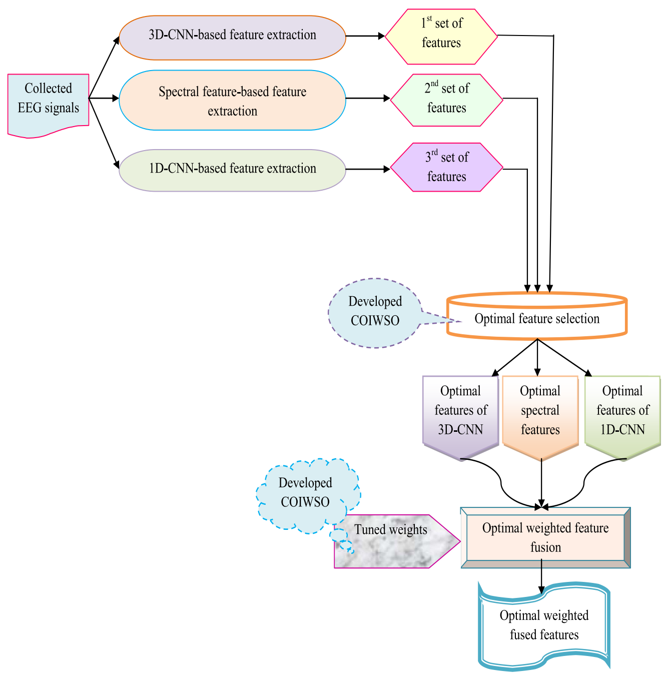

Fig. 3. Pictorial representation of optimal weighted feature fusion based on developed COIWSO.

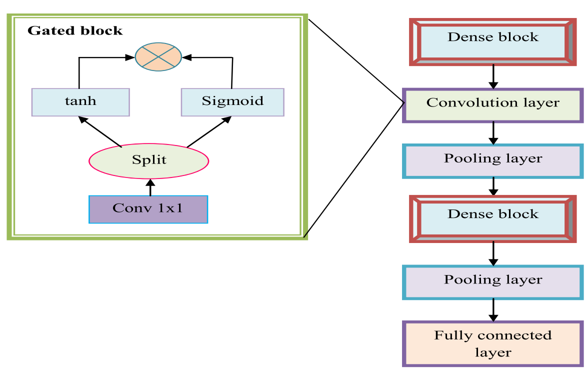

Fig. 4. Structural presentation of gated densenet architecture.

Here, the term FFu_g^{tn} indicates the fused weighted features and the optimized weights are presented as Wg_1, Wg_2 and Wg_3 by the suggested COIWSO. Here, the weights are tuned in the range $[0.01, 0.99]$ and ten optimal features are selected from each set of extracted features are tuned in the range [0, 29]. Further, the attained optimal weighted fused features FFu_g^{tn} are given as the input to the depression detection phase. The structural representation of optimal weighted feature fusion is presented in Fig. 3.

The fitness function of the optimal weighted feature fusion is to maximize the correlation among the weighted features offered in (13).

$$Ft_1 = \underset{\{OF_w^{3D-CNN}, OF_i^{1D-CNN}, OF_p^{stft}, Wg_1, Wg_2, Wg_3\}}{\arg\min} \left(\frac{1}{CRR}\right) \tag{13}$$

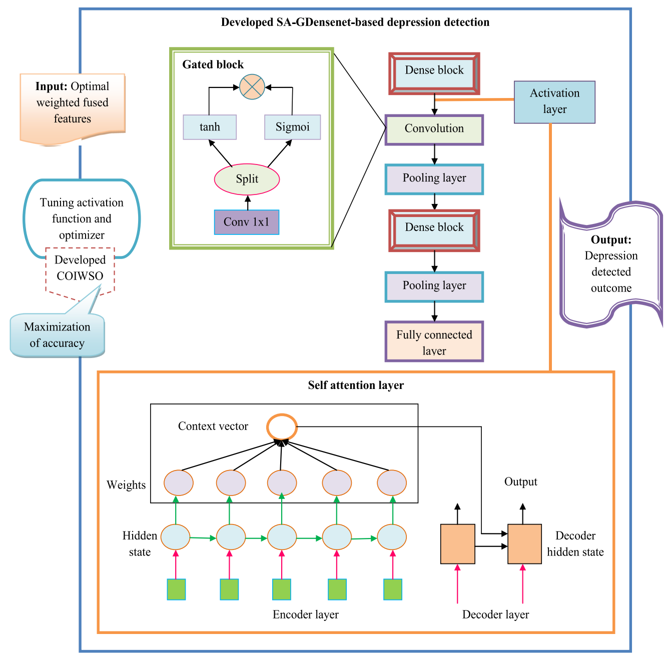

Fig. 5. Pictorial view of recommended SA-GDensenet-based depression detection model.

Here, the term *CRR* indicates the correlation coefficient. The correlation coefficient is determined using (14).

$$CRR = \frac{\sum\left(h_v - \bar{h}\right)\left(y_v - \bar{y}\right)}{\sqrt{\sum\left(h_v - \bar{h}\right)^2 \sum\left(y_v - \bar{y}\right)^2}} \tag{14}$$

The worth of h the variable attained in the features is referred to as h_v and their mean is termed as $\bar{h}$, sample value of y is offered as y_v and also the mean is provided as $\bar{y}$, in the above equation.

V. Depression Analysis Using EEG Signals by Extracting Three Sets of Features With Optimal Weighted Fused Features

A. Gated DenseNet Model

DenseNet architecture is based on densely connected patterns utilized to enhance the throughput of information flow in the network structure [33]. The architectural representation of the gated DenseNet is depicted in Fig. 4.

DenseNet connects entire layers directly in the feature map with equal size. A DenseNet can minimize the parameter count in the network, making training easier and eliminating redundant feature map learning. The DenseNet structure holds Z layers. Every layer denotes the composite operation set K_s, which holds different layers such as convolution, activation layer, batch normalization, and pooling layer. Here, the DenseNet links the entire layer with the succeeding layer, and also z^{th} layer gains a feature map of an existing layer as the input. The output of z^{th} layer is formulated in (15).

$$f_s = K_s\left[f_0, f_1, \ldots\ldots.., f_{s-1}\right] \tag{15}$$

The output zth is offered as f_s, the concatenation of the feature map from the entire previous map, and is termed as $[f_0, f_1, \ldots, f_{s-1}]$, the composite functions like activation function, batch normalization, and 3×3 convolutions are presented as K_s in-layer output. Additionally, the gating mechanism controls the flow of network information paths. Without the use of gates, stored information easily disappears during the transformation at each time step.

B. Self-Attention-Based Gated DenseNet Model

In general, diverse deep learning models have emerged, which promotes to provide sufficient performance. However, several techniques are not suitable for the long-term dependency problem. Therefore, the research work concentrates on the gated DenseNet model which has been adapted by the self-attention mechanism to provide better outcomes. Thus, it captures the long-term dependency and offers a better relationship in the input sequence. In this phase, the optimal fused features FFu_g^{tn} are given as the input to the depression detection phase. Employing the SA-GDenseNet model, the focus is on achieving an effective depression detection rate. By integrating an attention mechanism into the identification model, the aim is to detect depression in individuals with distinctive features. Widely adopted for establishing intra-dependency within sequence data [34], the self-attention scheme also serves to merge inner dependencies in the actual source and target source. The mathematical representation of the self-attention model is presented in (16).

$$HP = soft\max\left(\frac{\theta(Z)\,\emptyset(Z)^U}{\sqrt{k}}\right) \tag{16}$$

$$YR = HPy(Z) \tag{17}$$

Here, the input feature map is termed as *Z*, the affinity matrix is given as *HP,* and the feature amp output is presented as *YR*. Here, the entire features of *HP* trace the similarities between the two positions. Moreover, the self-attentions utilize two transform functions such as θ and ϕ transform the input to the minimal dimensional space. The internal products presented in the minimal dimensional space are utilized to validate the matrix of dense affinity *HP*. The term *k* indicates the scaling factor, which is used to resolve the small gradient issues in the softmax function, and the function *g* is employed to learn the effective embedding in the features. The diagrammatic view of developed SA-GDenseNet-based depression detection is offered in Fig. 5.

C. Self-Attention-Based Gated DenseNet Model With Parameter Optimization

In the depression detection model, the developed SA-GDenseNet is employed to detect depression among individuals using the input optimal features. The parameters in the gated densenet, such as the optimizer and activation functions, are tuned using the developed COIWSO. To improve the accuracy of depression identification, optimizers are adjusted within the range of (including Adam, SGD, Adadelta, and Ftrl) through the suggested COIWSO. Similarly, optimized activation functions are tuned within the range of (including ReLU, softmax, linear, and sigmoid) using the developed COIWSO. The objective function of the recommended SA-GDensenet aims to enhance the accuracy rate, as specified in (18).

$$Ft_2 = \underset{\{Op_a^{Gden},\, AF_c^{Gden}\}}{\arg\min}\left(\frac{1}{Auy}\right) \tag{18}$$

Here, the term Op_a^{Gden} indicates the optimizers and AF_c^{Gden} represents the activation functions. The term *Auy* denotes the accuracy and it is validated by the nearness of a particular value and its equation is represented in (19).

$$Auy = \frac{(xd + xf)}{(xd + xf + xg + xh)} \tag{19}$$

Here, the true negative is represented as *xf*, the true positive is represented as *xd*, the false negative is represented as *xh* and the false positive is represented as *xg*, respectively in the above equation.

VI. Results and Discussions

A. Experimental Setup

Various experimental analyses were conducted for the proposed depression detection model in Python. The developed model has experimented with a population count of 10 and a maximum iteration rate of 25 for effective analysis. Comparative analyses were performed against techniques such as the Jaya Algorithm (JA) [35], Deer Hunting Optimization Algorithms (DHOA) [36], COS [19], and IWO [29]. Additionally, comparisons were made with various classifiers, including Bidirectional Long Short-Term Memory (BiLSTM) [22], DNN [23], Support Vector Machines (SVM) [25], and SAB-DenseNet [33].

B. Performance Metrics

The performance measure used to analyze the implemented depression detection model is provided in [37].

C. Cost Function Analysis in the Developed Model

Examining Fig. 6 reveals an analysis of the cost function for the proposed depression detection framework, COIWSO-SA-GDenseNet. The convergence analysis carried out in this model yielded improvements of 19.04%, 15.01%, 26.08%, and 39.18% compared to JA-SA-GDensenet, DHOA-SA-GDensenet, COS-SA-GDenseNet, and IWO-SA-GDenseNet, respectively. Consequently, the suggested depression detection model demonstrates a superior convergence rate when compared to alternative methods.

D. Performance Analysis on Suggested Depression Detection Framework

In Figs. 7 and 8, various analyses are presented for the proposed depression detection scheme based on COIWSO-SA-GDenseNet. The accuracy analysis of the developed technique, utilizing 3D-CNN features, demonstrated improvements

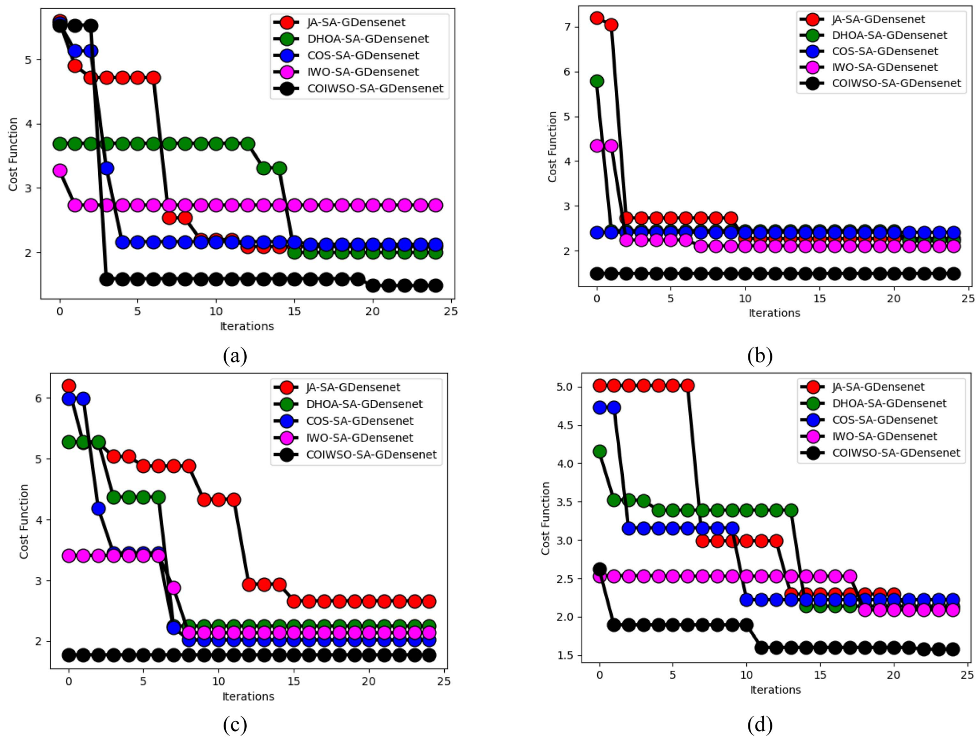

Fig. 6. Cost function analysis on developed COIWSO-SA-GDenseNet-based depression detection model with heuristic approaches over "(a) 1D-CNN features, (b) 3D-CNN features, (c) spectral features, and (d) fused features".

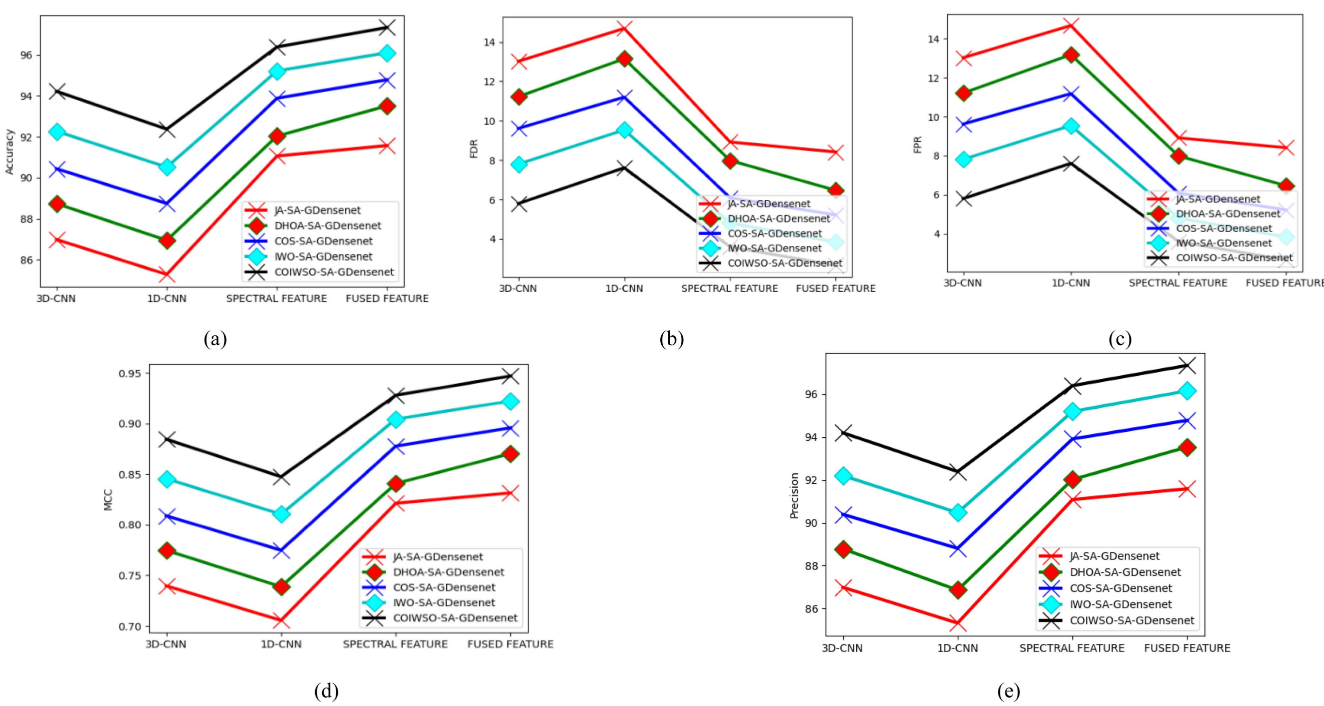

Fig. 7. Different analyses in developed COIWSO-SA-GDenseNet–based depression detection framework with heuristic approaches over "(a) accuracy, (b) FDR, (c) FPR, (d) MCC, and (e) precision".

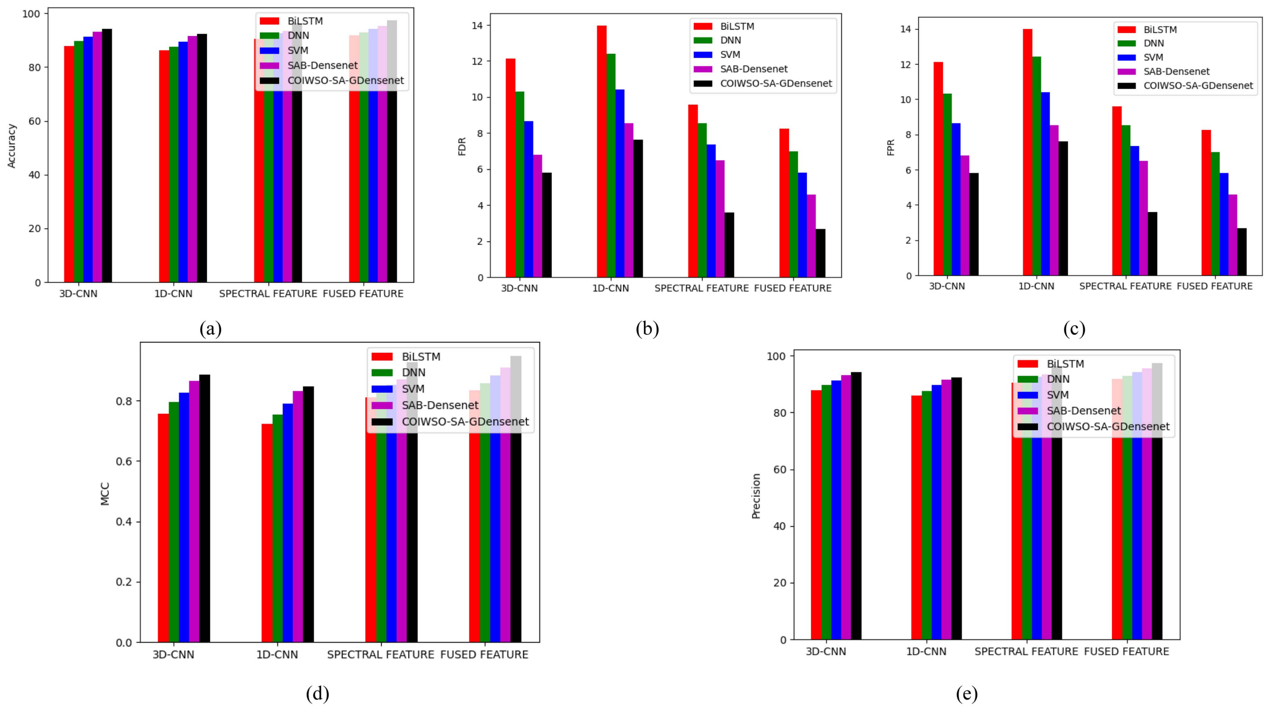

Fig. 8. Multiple analyses in developed COIWSO-SA-GDenseNet-based depression detection framework with existing depression identification techniques "(a) accuracy, (b) FDR, (c) FPR, (d) MCC, and (e) precision".

TABLE II
STATISTICAL ANALYSIS OF THE RECOMMENDED DEPRESSION DETECTION FRAMEWORK WITH DIFFERENT FEATURES OVER CONVENTIONAL HEURISTIC APPROACHES

Measures	JA-SA-GDenseNet [35]	DHOA-SA-GDenseNet [36]	COS-SA-GDenseNet [19]	IWO-SA-GDenseNet [29]	COIWSO-SA-GDenseNet
1D-CNN features-based analysis					
Worst	5.077849	4.604229	2.30351	4.805288	3.44295
Best	1.968984	2.175543	1.617311	1.605052	1.729184
Mean	2.670273	2.403321	1.754551	1.979316	1.846301
Median	1.984888	2.175543	1.617311	1.605052	1.729184
Standard Deviation	1.235797	0.59455	0.274479	0.95869	0.36503
3D-CNN features-based analysis					
Worst	3.480487	2.769031	5.104195	2.085935	2.176502
Best	2.144951	1.910372	1.639339	1.956054	1.792878
Mean	2.412058	2.272032	2.059442	1.997616	1.823568
Median	2.144951	1.981965	1.752974	1.956054	1.792878
Standard Deviation	0.534214	0.388543	0.820197	0.060586	0.104075
Spectral features-based analysis					
Worst	5.441026	2.907914	3.496105	5.077092	3.404539
Best	1.90939	1.801486	1.825301	1.700689	1.680789
Mean	2.261616	1.978514	2.079774	1.954817	1.883086
Median	1.967917	1.801486	1.825301	1.700689	1.680789
Standard Deviation	0.765168	0.405623	0.445254	0.736078	0.547903
Fused features-based analysis					
Worst	4.031722	4.505307	4.472316	2.195214	2.929038
Best	1.827011	1.843951	1.625814	1.722818	1.791487
Mean	2.274125	2.311585	2.037875	1.952674	1.895817
Median	1.827011	2.145459	1.625814	1.964561	1.86152
Standard Deviation	0.790183	0.804852	0.684348	0.156603	0.212123

of 15.85%, 14.45%, 13.09%, and 10.46% compared to conventional approaches, namely JA-SA-GDenseNet, DHOA-SA-GDenseNet, COS-SA-GDenseNet, and IWO-SA-GDenseNet, respectively. Similarly, the precision analysis of the suggested depression detection model showed enhanced outcomes of 8.6%, 5.9%, 3.8%, and 0.1% compared to BiLSTM, DNN, SVM, and SAB-DenseNet models, respectively, considering the 1D-CNN feature. Consequently, the recommended depression classification model achieved a higher depression detection rate.

E. Statistical Analysis on Developed Depression Detection Model Over Baseline Heuristic Approaches

Statistical analyses of the COIWSO-SA-GDenseNet-based depression detection model are presented in Table II. The

TABLE III
COMPARATIVE ANALYSIS OF THE RECOMMENDED DEPRESSION DETECTION FRAMEWORK

TERMS	FCL [40]	CNN+LSTM [41]	COIWSO-SA-GDenseNet
Accuracy	85.14	86.89	94.49
Precision	85.63	87.09	94.64
FPR	14.67	13.28	5.51
FDR	14.37	12.91	5.36
MCC	70.29	73.77	88.97

optimal analysis within the suggested depression detection framework yields improved performance of 1.94%, 2.84%, 10.19%, and 1.9% compared to traditional heuristic models, namely JA-SA-GDenseNet, DHOA-SA-GDenseNet, COS-SA-GDenseNet, and IWO-SA-GDenseNet, respectively. Consequently, the developed depression identification framework demonstrated a superior depression detection rate compared to alternative models.

F. Comparative Analysis of the Developed Model

The comparative analysis of the developed model for mental depression is shown in Table III. Here, the performance shows that the developed model offers 94%, which is better than the existing approaches. Throughout the validation, the developed model shows superiority over other existing approaches.

VII. CONCLUSION

Advanced depression detection framework employs metaheuristic techniques to enhance the accuracy of detecting depression in affected individuals. EEG signals from a standard benchmark serve as input for analysis, leading to three sets of features as output through the feature extraction process. The first set of features is derived from EEG signals, converted into spectrogram images, and input to 3D-CNN. These features are then directed to the optimal weighted feature fusion region. Similarly, the second set of features, obtained through an EEG signal input to 1D-CNN, is also fed into the optimal weighted feature fusion. Lastly, the third set of spectral features, acquired from original EEG signals, undergoes the same process. Optimal weighted feature fusion is executed by the developed COIWSO using the three sets of extracted features. The resulting optimal weighted features are employed in the depression detection phase. The SA-GDensenet is utilized to identify depression among individuals. Tuning of the gated densenet parameters was achieved through the developed COIWSO to attain the maximum accurate depression detection rate. Accuracy analysis within the developed COIWSO-SA-GDensenet-based depression identification technique demonstrates improvements over conventional approaches such as JA-SA-GDensenet, DHOA-SA-GDensenet, COS-SA-GDensenet, and IWO-SA-GDensenet, with gains of 15.85%, 14.45%, 13.09%, and 10.46%, respectively. Precision analysis in the suggested depression detection model, focusing on 1D-CNN features, exhibits an 8.6% improvement over BiLSTM, 5.9% superiority to DNN, 3.80% advancement compared to SVM, and a 0.10% improvement over SAB-Densenet. Therefore, the recommended depression detection framework has shown its higher efficacy on the early identification of depression among individuals. In real-world applications, mobile based applications are performed to detect mental illness. Here, the patient needs to be monitored with 24×7 hours to analyze the mental illness from the particular individual. Moreover, real-world applications of several mobile-based applications and healthcare applications are performed where they can be applicable in the clinical field.

Potential limitations include concerns about dataset diversity, sensitivity to optimization techniques, model interpretability, and generalizability. It is required to have diverse datasets, robust optimization methods, improved model interpretability, and exploration of broader applications.

A. Policy Implications

The detection of mental health disorders becomes very essential where untreated mental disorders could cause unnecessary disability, suicide, and poor quality of life. However, the significant policy implications in mental disorders help to promote the mental health of every individual. Some of the political beliefs could affect the relationship between mental health and exposure, and several social media sites were utilized to identify the groups in the political environments. Moreover, the several youth development policies and other related programs for mental health disorders in adolescents.

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