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Elucidation of Multi-dimensional input Efficient Attention Network and Improved Heuristic Approach with Multimodal Data Source for Depression Classification

B. Manjulatha[1], Suresh Pabboju[2]

[1]*Department of CSE, Osmania University Vignana Bharathi Institute of Technology Hyderabad, Telangana, India manjulathakbr@gmail.com*
[2]*Department of Information Technology Chaitanya Bharathi Institute of Technology Gandipet, Hyderabad, Telangana, India plpsuresh@gmail.com*

Depression is an ordinary mental illness that affects a person's capability to think deeply and grow mentally. A person's beliefs, behaviors, feelings, and overall sense of well-being are affected by depression, which is characterized by a poor mood and dislike of behavior. Depression is a severe mental illness that causes mental disorders by decreasing the ability to think and feel at work, school, and in the family. Depression results in extreme anxiety or even suicidal thoughts. Currently, there are numerous applications for accurately assessing and ensuring depression levels. Therefore, it is critical to identify depression in the early stage. Since depressions are associated with a variety of human qualities and multimodal data are needed for the categorization phase. Hence, a multi-dimensional deep learning network using multimodal data sources is developed to classify the depression states accurately. Initially, three different data forms like text, signal, and video are accumulated from the benchmark datasets. The input text data are given to Bidirectional Encoder Representations from Transformers (BERT), in which the text features are attained in the form of 1D. Further, the input signal is converted into spectrograms that are represented in 2D. Then, the input video is considered, in which it contains the frames of 3D form. At the final stage, these three different dimensional sources are subjected to a Multi-dimensional input Efficient Attention Network (MEANet) for classifying the depression state. The three different dimensional features act as the multidimensional process. For further increasing the efficiency, the hyperparameters of MEANet are optimally selected by using Mutated Fitness-based Squid Game Optimizer (MF-SGO). Thus, the classification efficiency of the proposed model is examined using distinct metrics and compared with other baseline models. Hence, the extensive results demonstrate that the proposed classification system renders higher results in enhancing performance.

Keywords: Depression Classification; Multi-dimensional Input; Efficient Attention Network; Bidirectional Encoder Representations from Transformers; Mutated Fitness-based Squid Game Optimizer;.

1. Introduction

Depression is a mental disorder, which is characterized by enduring sadness, despair, and a loss of interest in once-enjoyable activities [9]. It may have an impact on a person's day-to-day functioning, which results in a range of psychological and medical issues. Depression has a significant psychological effect on individuals [10]. People who suffer from depression find it more difficult to focus on their work. These factors have a significant impact on these people's lives. Depression emerges in a variety of ways and affects people differently [11]. Its symptoms vary from moderate to severe and may involve mental, emotional, and physical problems [12]. Based on the severity, the depression is classified into mild depression and moderate depression. Mild depression is characterized by a lack of interest in one's environment that has no major impact on everyday life, learning, or social relationships [13]. Moderate depression is characterized by emotional oscillations, a depressed mental state, and delayed thinking that has an impact on professional life. It is very essential to diagnose depression in its early stage [14]. An accurate diagnosis assists in generating individualized treatment strategies based on the unique kind and severity of depression, resulting in more effective outcomes [15]. Effectively identifying and treating depression appreciably boost a quality of person life by reducing symptoms, and boosting a sense of happiness [16].

Several studies have been undertaken on depression. Neuroimaging approaches such as functional Magnetic Resonance Imaging (fMRI) have assisted researchers in understanding the neural structure of depression [17]. Resting-state fMRI studies have identified alterations in neural connectivity in patients with depression, providing useful information about the neural causes of the disorder [18]. Graph theory analysis of brain networks is used to analyze the changes in neural connectivity between people with depression. These investigations found variations in network features, such as characteristic path length and clustering coefficient of persons with depression [19]. Electroencephalography (EEG) signals have been used in depression studies to investigate brain activity and correlated patterns. Recent research has investigated the use of EEG data and functional connectivity matrices for depression recognition, indicating the potential of deep learning systems like Convolutional Neural Networks (CNNs) in categorizing moderate depression based on EEG signals [20]. Machine learning approaches, including neural networks have shown promising results in detecting symptoms and patterns linked to depression. These approaches provide potential for building objective and data-driven tools to diagnose and monitor depression.

Deep learning-based depression categorization is an integration of sophisticated deep learning algorithms to examine numerous data sources and categorize individuals based on their chance of experiencing depression. This method employs deep neural networks for extracting and categorizing features, resulting in a more accurate and efficient diagnosis of depression symptoms. This model evaluates a variety of data types, including speech signals, online behavior, and social media activity to detect patterns linked with depression. Using this neural network, the complicated representations from big datasets are analyzed and increase the probability of depression assessment. Yet, this method requires a significant volume of high-quality data to train. Obtaining labeled datasets for depression classification is difficult because of issues related to privacy, and data error. Overfitting to training data and a lack of capacity for alterations in input data negatively affect the ability of depression categorizing techniques. Therefore, an efficient depression categorization model is developed in this proposed work.

The main contributions of the designed categorization of the depression framework is provided in the below points.

To develop a deep network that revealed an excellent strategy for categorizing depression from patients using text data, EEG signals, and video. This method used a variety of strategies, including differential entropy for feature extraction, a genetic algorithm, and a neural network for classification.

To implement BERT for identifying the effective feature from the text data. By introducing a feature extraction process, this suggested model intended to improve the retrieved features' discriminatory power in identifying depressed patients based on their text data to emotional stimuli.

The use of the STFT strategy to enhance spatial differences in EEG signal before feature extraction considerably improved the ability to classify depressed patients, particularly in reaction to positive and negative emotions.

To design an MF-SGO algorithm that optimally tunes the variables from MEANet, this increases the predictability of the depression recognition model. The objective of optimally tuning the variable is maximization of accuracy and precision.

To design a MEANet structure with the goal of improving depression patients' categorization accuracy in response to positive and negative emotional stimuli. This network is formed by merging multiple input layers with attention layer to capture the relevant information. It emphasizes the necessity of addressing spatial information in EEG-based classification tasks for diagnosing depression.

Experimental analysis illustrates the significance of processing information to improve the success rate of depression detection models, specifically the role of deep learning techniques in dealing with complicated datasets.

The overall structure of the proposed model is provided in the below sections. Section II provides the overview of the literature survey along with a discussion of existing techniques' benefits and challenges. Efficient depression categorization model architecture is presented in Section III. The design idea for data acquisition, feature extraction, and the flow of data processing are explained in Section IV. Section V outlines the classification steps from multi-modal data using deep networks. Finally, the discussion and summary of the results of this study are specified in Section VI and Section VII, correspondingly.

2. Literature Survey

A. Related Works

In 2020, Ding et al. [1] have extracted features from complex original data that was gathered from Weibo using a traditional neural network. This model attempted to detect depression for college students through their online behavior patterns by combining deep brain neural networks and support vector techniques. The construction of a specific detection model using deep strategies in practice, and theoretical analysis combined to make the presented work valuable for both psychological research and medical technology.

In 2021, Jiang et al. [2] have improved the ability of classification using spatial information collected from EEG signals. It significantly increases the spatial variations without feature extraction, which enhances the quality of classification for the diagnosis of depression in patients. This framework also emphasized the need of deep acquisition and transfer of learning methodologies for future research and demonstrated a dedication to developing the field of EEG-based diagnosis of depression.

In 2023, Amram et al. [3] have presented a novel intelligence-based method for identifying and categorizing mental health disorders, with a particular emphasis on depression. This model enhanced the understanding of psychological problems but also showed how computing technology was used to derive useful insights from texts while reducing the personal nature and mistakes of traditional analysis techniques.

In 2022, Schultebraucks et al. [4] have proposed a deep learning system for the assessment of visual and auditory signals in order to predict the mental health of trauma survivors. The goal of this model was to simplify and expand clinical assessment procedure by combining "speech content analysis, voice prosody, and face emotion expression". This finding showed that deep learning models have the capacity to measure clinical functioning precisely and offer a more reliable and ecologically sound approach to risk assessment from unstructured data sources. It also emphasized the value of digital biomarkers in remote assessment, especially in situations when people might far from suitable therapeutic care, like in trauma or disaster-affected areas.

In 2020, Li et al. [5] have suggested a novel method for learning and identifying patterns in functional connectivity matrices unique to people with mild depression using a CNN. This computer-aided approach had the potential to identify moderate depression patients more quickly, allowing for early detection and treatment. This suggested framework demonstrated how modern computational techniques improved the detection capability of mental health issues like mild depression.

In 2020, Zhu et al. [6] have developed a better classification model that uses EEG and eye-tracking data to detect depression. This suggested Content-Based Ensemble Technique (CBEM) efficiently combines data from both EEG and eye movements to improve the rate of depression prediction. This innovative method offers a valid and impartial assessment technique for identifying depression, which could have major implications for early identification and treatment in the field of mental health.

In 2020, Khosla et al. [7] have proposed a comprehensive analysis of signal processing models for various applications based on EEG signals. This research comprised a broad spectrum of applications such as the identification of neurological conditions. Brain signals from several modalities were merged to highlights the drawbacks of existing fusion methods and the proposed, latent correlation embedded multi-modal fusion (LLM2F) algorithm to address these limitations.

In 2022, Zhang et al. [8] have created an adaptive Auto Regression (AR) model for EEG features and linear EEG for features extraction. To achieve data diversity, graph metric characteristics in depression-related brain areas and EEG features associated with depression were chosen as the multimodal fusion database. The decision-level computer-assisted depression assessment model was realized based on the principle of fusion techniques. The results of multi-group controlled trials demonstrated that the recommended model had higher ability to recognize.

B. Problem statement

Classifying depression, especially with the support of modern technologies has great potential for changing mental health services. Healthcare professionals are able to produce individualized treatment programs for patients with depression using classification models. Personalized therapy techniques are developed to enhance patient happiness and improve the outcomes by classifying patients according to their symptoms, risk factors, and responsiveness to therapies. Privacy and ethical issues are the challenging processes that must be resolved for effective depression classification. Some of the existing challenges in depression classification are provided in the below points.

Existing models need a lot of high-quality labeled data. Due to the complex nature of mental health data and the requirement for expert labeling, getting well-annotated datasets in the context of depression categorization is difficult.

Brain activity varies among individuals based on electrode location and signal noise. It is difficult to obtain reliable features for categorization because of this variation in existing models.

In existing models, preprocessing of EEG data is extremely time-consuming and requires precise optimization to maintain pertinent information while lowering noise.

In existing models, it is essential to address data bias using appropriate and diverse datasets in order to ensure the accuracy of unbiased classification outcomes.

Privacy issues arise when sensitive data are gathered and analyzed for the purpose of classifying depression. So, it is important to safeguard people's right to privacy, ensure data security, and get informed permission before gathering information, which are challenging tasks while classifying depression.

The features and challenges of the existing depression classification model are provided in Table I.

TABLE I. FEATURES AND CHALLENGES OF THE EXISTING DEPRESSION CLASSIFICATION MODELS

Author [citation]	Methodology	Features	Challenges
Ding et al. [1]	Neural network	• This method has the capability to capture minute patterns and intricacies in signals or data regarding depression because it automatically extracts pertinent information from high-dimensional data.	• Training neural networks are extremely computational, requiring strong hardware and a substantial amount of time.
Jiang et al. [2]	TCSP	• TCSP elevates the classification accuracy of EEG data by extracting task-specific spatial characteristics that are important for depression classification.	• TCSP might require extensive computational resources, particularly when interacting with huge datasets or complex EEG signals

Amram et al. [3]	SVM	• This method is suitable for accurately tracking the patient's improvement over time. This aids in altering treatment strategies as necessary.	• Several ethical concerns about privacy, permission, and proper handling of mental health themes are challenging tasks.
Schultebraucks et al. [4]	ML	• This model offers a computer-based and scalable approach to forecasting psychological wellness in trauma survivors.	• This model displayed significant predictive ability. Still, it has negative aspects when evaluating univariate relationships.
Li et al. [5]	CNN	• This method creates hierarchical features from raw data, making them well-suited to handling complicated EEG signals and retrieving key depression-related patterns.	• High operational cost and limited memory are the difficulties faced in CNN structure.
Zhu et al. [6]	CBEM	• This method uses valuable data from many modalities, which leads to more accurate and trustworthy predictions.	• It is harder to interpret than other classic classification models
Khosla et al. [7]	BCI	• It is operationally less intensive and demands fewer resources for storage.	• Integrating neurological signals from various neuroimaging modalities creates ethical issues.
Zhang et al. [8]	DL	• It is very reliable and provides strong forecasts.	• Overfitting issues are high in neural networks.

3. An Efficient Depression Classification Framework from Multi-Modal Data: Architecture and Dataset Description

A. An Efficient Depression Classification Model: Structural View

Depression classification is the process of categorizing individuals into groups based on their possibility of having depression. Healthcare experts can provide effective treatment plans to patients by accurately classifying the individuals based on their depression status. Symptoms might interfere with daily life and include changes in hunger, sleep difficulties, exhaustion, and feeling worthless. Psychotic depression is an extreme case of depression characterized by psychotic symptoms such as delusions and hallucinations. Deep learning is used to evaluate and classify data linked to depression symptoms, behaviors, and associated risks. This method is capable of recovering intricate patterns and features from large datasets, allowing for more accurate categorization of depression levels or the identification of individuals at risk. Textual data from social media platforms like Twitter, Facebook, or online forums might reveal details about an individual's state of mind, behavior habits, and mental health. EEG signals are capable of providing anatomical structure brain data, which reveal neurological function related to depression. Various noises and artifacts are influenced by EEG signals. Ensuring the quality and reliability of EEG data for classification purposes are difficult task. Ensuring the ethical concerns of EEG data for depression classification is a challenging task. Therefore, an effective multi-modal data source-based depression classification model is developed. The architectural view of the proposed model is provided in Fig. 1.

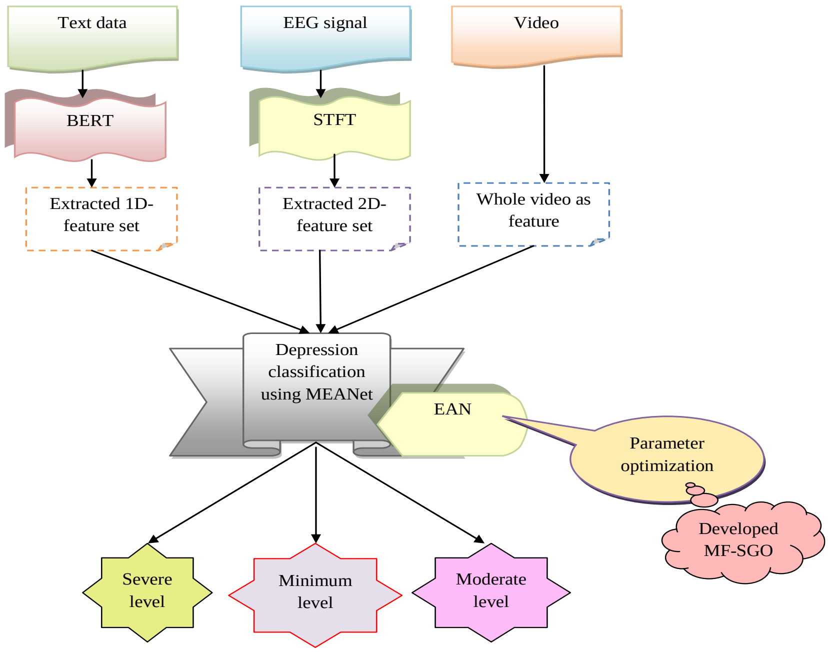


Fig. 1. Architectural view of proposed depression categorization model using deep learning

An effective deep learning-based depression categorization model is developed with multi-dimensional input for accurately classifying individuals with depression. The use of deep learning allows the integration of numerous data modalities including text data, EEG signal, and video for complete depression categorization. Multi-modal techniques offer a deeper understanding of a person's mental health. These multi-modal inputs are accumulated from the standard database and the deep features from these inputs are extracted for future depression categorization. Deep techniques like BERT and STFT automatically extract relevant characteristics from raw data, EEG signals, and video. This might be vital in recognizing trends associated with depression. BERT extracts key characteristics and trends from the input data, allowing the model to develop valuable representations and carry out accurate categorization. STFT extracts essential elements from EEG signals for depression categorization. Selecting the optimal features is critical to ensure that the features obtained reflect the most informative parts of EEG data, allowing for accurate and trustworthy analysis. Most significant features from videos are utilized to acquire data regarding psychological disorders. Finally, depression classification is performed based on these accumulated features and ensures that the extracted features capture significant information about the emotional states, behavioral signals, and physical reactions associated with depression. An appropriate deep model MEANet performs depression level rating. The designed model improves the accuracy and adaptability of actually unseen data by fine-tuning the MEANet model variables through the MF-SGO algorithm. Confirm the trained model against an independent validation dataset to ensure its ability to generalize the new data. Interpret the method of classification findings determine the relevance of various factors in predicting depression.

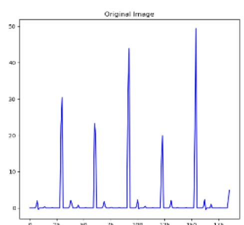
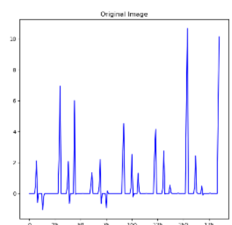
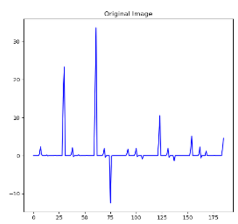
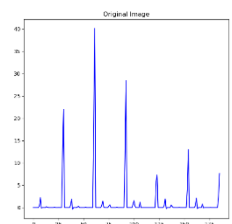
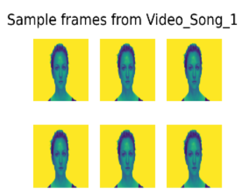
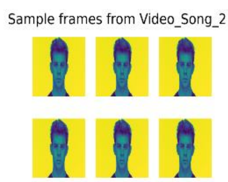
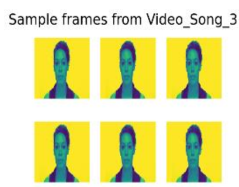
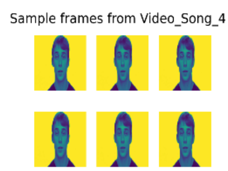
B. Elucidation of Depression Dataset

The description related to multimodal data sources for the classification of depression is provided in the below points.

Text files dataset ("Suicide and Depression Detection"): The text data related to depression posts are collected from the link "https://www.kaggle.com/datasets/nikhileswarkomati/suicide-watch" accessed on 2024-06-24. Here, the posts are composed using "Pushshift API". The observations of behavior and emotional responses in controlled settings to provide input for classification. This current version has both suicide posts and non-suicide posts. Finally, collected text data is represented as . Where, the term is denoted as , which represents the entire amount of data collected for processing.

EEG signal dataset ("Depression Dataset Preprocessed"): The EEG signal required for depression analysis is gathered from the standard database and the link is "https://www.kaggle.com/datasets/tocodeforsoul/depression-rest-preprocessed" accessed on 2024-06-24. This site provided depression rest EEG signals with their rating level of depression. The total score of 0-13 range is considered as minimal range, 14-19 range is indicated as moderate and 29-63 ranges are considered as severe level. By using these EEG signal ranges the functional connectivity matrices represent brain activity pattern to classify individuals with varying levels of depression. The gathered EEG signal is represented as for the assessment of the depressed person.

Video Dataset: The audio needed for this research work are collected from the link "https://zenodo.org/record/118897 accessed on 2024-06-24". The audio used in this proposed work is symbolized as from "RADVDESS" for the assessment of an individual's mental health. The sample video is converted into several frames. By splitting the video into individual frames, a more detailed and precise analysis is carriedout. Individual frames are preserved and retrieved more relevant information, which is valuable for the classification of depressed person.

<table>
<tr><td>EEG signal</td><td></td><td></td><td></td><td></td></tr>
<tr><td>Video signal</td><td></td><td></td><td></td><td></td></tr>
<tr><td>Text data</td><td colspan="2">Sucide:
1. "Not depressed or sad but getting more comfortable</td><td colspan="2">Non- Suicide
1. "Today's fact is Reddit awards are expensive emojis"</td></tr>
</table>

	with suicide day by day because I just do not enjoy the struggle of being alive". 2. "Excuse for self inflicted burns I do know the crisis line and used it after when I was having a panic attack".	2. "Am I weird I don't get affected by compliments if it's coming from someone I know irl but I feel really good when internet strangers do it"

Fig. 2. Sample images collected from the dataset

4. Extraction Of Features From Multi-Modal Input Data To Improve Depression Classification Performance

A. BERT-based Text Feature Extraction

The collected input text data is indicated as , which is applied to BERT [34] for the extraction of relevant features. It converts the incoming text data into different tokens using the WordPiece tokenization strategy. Contextualized word embeddings are produced by feeding the encoded input into the BERT model that is already been trained. BERT analyzes the surrounding words in a sentence to determine the context of each word. To extract features from BERT embeddings, several pooling strategies based on the task are used. For sentence-level problems, common solutions are to use CLS token embedding, and for word-level tasks, average token embeddings is employed. Compared to more conventional word embeddings like "Word2Vec or GloVe", BERT provides more meaningful word embeddings by capturing the wider context of words in a phrase. BERT performs transfer learning for tasks that require less labeled data in the future because it has been pre-trained on a significant amount of textual data.

BERT automatically creates integrated embeddings for words or phrases. It does not require considerable feature engineering and lessens the amount of human labor needed for feature design. By using BERT-based feature extraction, the designed model benefits from the advanced language understanding capabilities of BERT and achieves high accuracy on tasks. Through numerous layers of transformer blocks, BERT processes the token embeddings with positional encoding in order to extract contextual information about each word depending on the words that surround it in the phrase. By exploiting contextual representations, BERT effectively manages conceptual differences across domains. This aids in capturing the different interpretations of text in various circumstances. Finally, the extracted text feature set 1 is in 1Dimensional (1D) format, which is used for the further classification process.

B. STFT-based Spectrogram Conversion

The gathered EEG signal is applied to STFT [35] for examining non-stationary signals. It makes it possible to analyze changes in the signal with time and frequency. Temporal events and frequency components are identified using the time-frequency representation of EEG signals that STFT gives. STFT captures brief variations in EEG signals because it localizes signal components in both the temporal and frequency domains. It allows the frequency content of a signal to vary over time by performing the Fourier transform of short, overlapping segments. This enables the acquisition of time-varying frequency information, which is not achievable with the standard Fourier function. STFT works by applying a window function to the signal to isolate short segments, which are subsequently Fourier-transformed. This is mathematically expressed in Eq. (1).

$$B(y) = S(\pi, \upsilon) = \int_{-\alpha}^{\alpha} B(y) w(y-\pi) e^{-ket} dt \qquad (1)$$

Here, the original signal in the time domain is indicated as and the window function is . The frequency parameter and lag parameter are represented as and , respectively. STFT generates a spectrogram by extending the window function throughout the signal and evaluating the Fourier transform for each segment, demonstrating how the signal's frequency content changes over time. This analyzes the trade-off among time localization and resolution of frequency using the window function. The spectrogram created from the STFT is useful for feature extraction in EEG signals, as it allows the detection of certain frequency elements at different time points within the signal. Finally, the extracted feature set 2 is in the 2D format.

C. Conversion of Video into Frames

Video input is indicated as for the extraction of features. Converting a video into frames is the initial step in extracting features from every frame. Once the frames are collected has the capability of processing them to extract features. By splitting the video into individual frames, a more detailed and precise analysis is performed. Individual frames are preserved and retrieved more efficiently at precise time points, which is valuable for applications that need access to certain areas of the video. Frames can be categorized and searched using extracted features, allowing for quick identification of relevant frames. Finally, the extracted feature set 3 is in the 3D format. The overall feature extraction diagram is provided in Fig. 3.

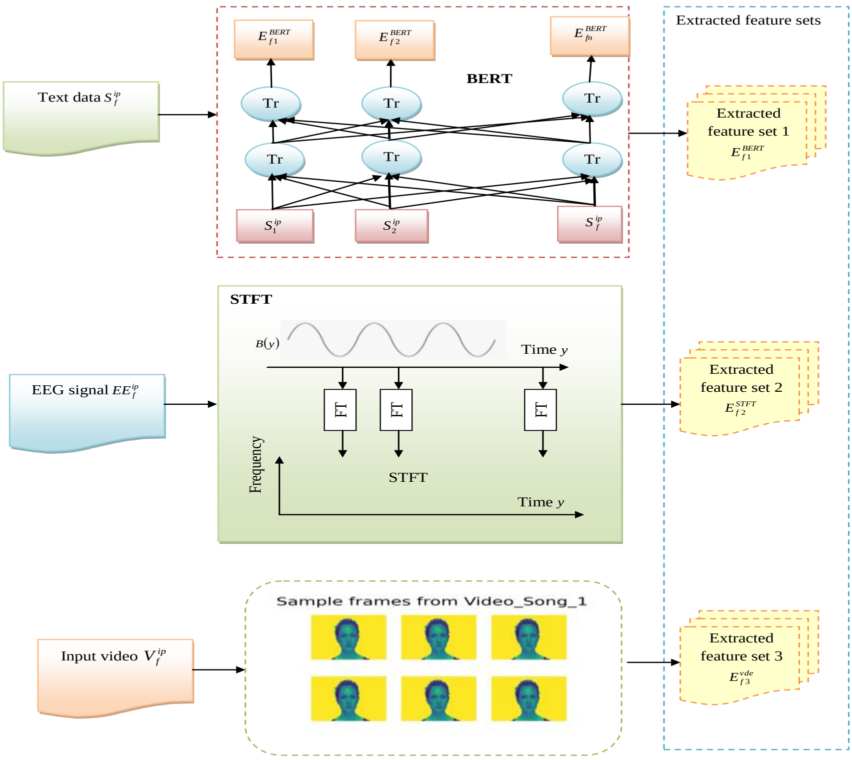


Fig. 3. Overall Feature Extraction Diagram

5. Depression Classification Steps from Multi-Modal Data Using Multi-Dimensional Attention-Embedded Deep Network

A. Efficient Attention Network Description

An efficient attention network learns multi-dimensional features from a single layer as well as local characteristics from many layers. The multi-dimensional module included in an efficient network promotes the model to learn features of different scales by separating the same features of different scales via pooling operations. 1D, 2D and 3D inputs are applied to efficient attention network for capturing most relevant parts of the inputs, and reduce the computational load. The attention module incorporates both spatial and channel attention. Assigning different weights to channels based on their relevance levels. This strategy highlights selective channels while comprising less informative ones, allowing the model to focus on essential characteristics and regions inside the face image efficiently. It is intended to improve efficacy by combining spatial and channel attention. It reduces the computing effort needed for fusion and enables the model to focus on specific characteristics efficiently. The attention processes in an efficient network assist in focusing on essential regions and features within the face image, resulting in better results for the recognition of depression tasks. It improves the accuracy and recognition results by leveraging attention processes efficiently. It provides greater concentration on crucial characteristics, enhanced performance in face recognition tasks, successful computational interpreting, flexible feature fusion, and targeted model training, making it an effective strategy for a reliable and precise depression identification system. The general architecture of an efficient attention network is specified in Fig.4.

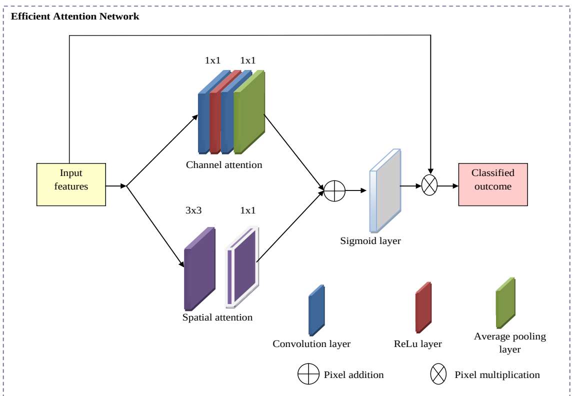


Fig. 4. Basic architecture of Efficient Attention Network

B. Depression Classification using MEANet

Designed MEANet for depression categorization to handle multimodal input data such as video, EEG, and text in order to identify complex patterns linked with depression. This entails creating a neural network capable of processing and integrating many forms of incoming data efficiently. Multi-dimensional inputs like “text data, EEG signal, and video” are used in this analysis. The text data is processed and extract features with embeddings such as BERT. The input video is splitted into number of frames for extracting the relevant features suitable for depression categorization. EEG signals are used to determine patterns associated with cognitive states, neurological diseases, and brain activity. The selection of acceptable features is influenced by the unique application demands. These extracted multidimensional features like 1-D feature , 2-D feature , and 3-D whole video feature are applied to MEANet for the categorization of depression. This multi-dimensional input such as 1D, 2D and 3D integrates multi-modal data using the efficient attention mechanism. This approach helps to capture diverse aspects of depressive symptoms by managing computational complexity. It handles large scale data efficiently and boosts the accuracy of depression detection, upgrade early diagnosis and personalized treatment strategies. MEANet structure is formed by adding multiple input layers to handle several data modalities. By mixing attributes from several modalities, MEANet is able to access data-rich contextual information, resulting in higher-quality and robust forecasts. Attention layers in MEANet prioritize key features from each modality. The fusion layer combines or fuses the outputs from the various modalities. Finally, fully connected layers perform the final depression categorization and categorize the depression stages into minimum, moderate and sever. The reliability of the designed model is enhanced by optimizing the attributes like "hidden neuron count, epoch count, and step per epoch" from MEANet. The aim of optimization is the" maximization of accuracy and precision" of the depression classification process. The objective function is mathematically expressed in Eq. (2).

$$W_{obj} = \underset{\{Nc^{MEAnet}, Ec^{MEANet}, Sp^{MEANet}\}}{\arg\min}\left(\frac{1}{Ar + Ps}\right) \qquad (2)$$

Here, the term Nc^{MEAnet} is indicated as optimized hidden neuron count that varies in the range of $[5-225]$, Ec^{MEANet} is the optimized epoch count varies in the range of $[5-50]$, and Sp^{MEANet} is the optimized step per epoch count that varies in the range of $[100-500]$. The accuracy and precision are represented as Ar and Ps, respectively. The statistical form of accuracy and precision are mentioned in the below equations.

$$Ay = \frac{R_* + H_*}{R_* + H_* + Q_* + B_*} \qquad (3)$$

$$Ps = \frac{R_*}{R_* + Q_*} \qquad (4)$$

Here, the true positive and negative values are indicated as and , respectively. The false positive and negative value is specified as and , correspondingly. By using efficient attention mechanisms, this network is able to process incoming data in faster, making it suited for real-time applications such as continuous monitoring and interaction. In telemedicine or mental health apps, MEANet provides current insight into a person's mental state, allowing for immediate actions. MEANet provides a sophisticated and adaptable approach to depression categorization and other complicated tasks. Its ability to combine and quickly process multimodal data, together with the accessibility and robustness offered by attention mechanisms, makes it an important tool in both clinical and research settings. The proposed architecture of MEANet-based depression classification is given in Fig. 5.

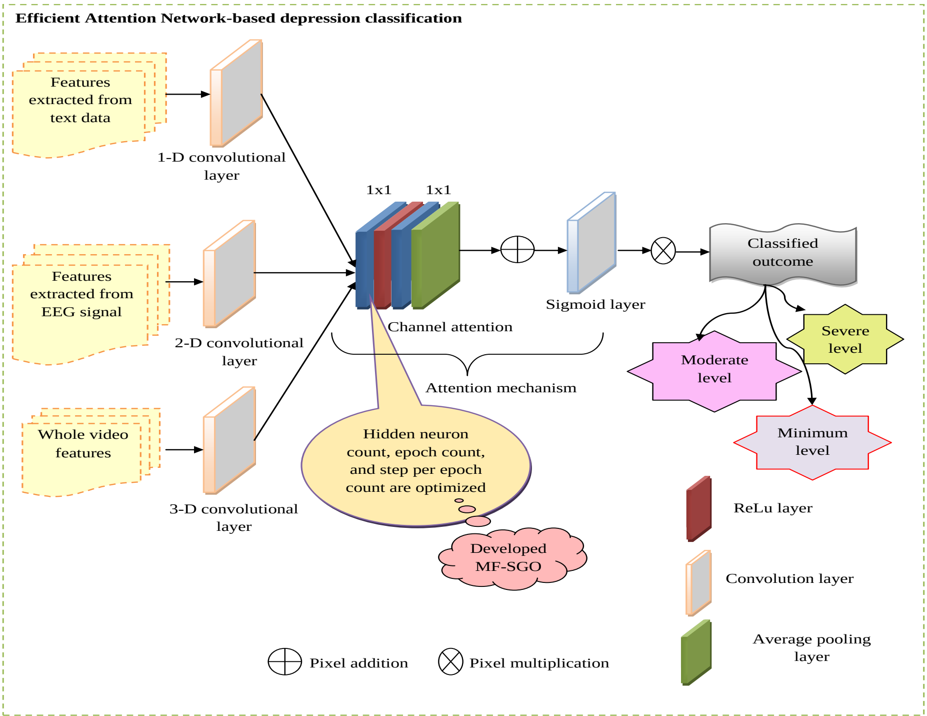


Fig. 5. Proposed MEANet-based depression classification model

C. Parameter Tuning using Presented MF-SGO

MF-SGO algorithm is designed in this framework for tuning the attributes like "hidden neuron count, number of epoch count, and step per epoch count" from MEANet. Fine-tuning the attributes helps to attain a better classified outcome in terms of accuracy and precision. MF-SGO algorithm is stable and scalable, allowing handling various levels of difficulty and dimensions that boost the reliability of categorization phase. Conventional SGO algorithms are expensive to compute, particularly if there are many agents (players) and iterations result in longer computation time and higher utilization of resources. When compared to other well-known optimization methods, SGO is not the most efficient option in terms of convergence time and processing overhead. Hence, SGO algorithm is modified by upgrading the random variable in Eq. (6) using the developed concept provided in Eq. (2). Current fitness value, mean fitness, and worst fitness are evaluated to upgrade the random variable. The statistical form of upgrading random variable is provided in Eq. (5).

$$K_r = \frac{F_c}{(F_m + F_w)} \quad (5)$$

Here, the terms F_c, F_m and F_w are indicated as current fitness, mean fitness, and worst fitness values. MF-SGO outperformed better than other well-known metaheuristics on a wide range of optimization problems and has the capability of finding solutions of excellent quality at faster convergence rates than other algorithms. It is stable and scalable, allowing it to handle optimal operation problems of various levels of difficulty and dimensions. MF-SGO demonstrated outstanding results in converging to global best solutions in the majority of classification phases.

SGO [26]: It is a novel metaheuristic optimization algorithm enthused by the main rules of the classic Korean game known as the "squid game". In the multiplayer mode of the squid game, players fight with one another to accomplish their objectives. The populations of candidate solutions are classified into offensive and defensive players. In order to find the optimum solution, the offensive players fight with the defensive players based on their fitness values. Using a novel strategy, the SGO algorithm sets offensive players against defensive players, and the winner of the match is the one with the highest fitness value. It determines the best solution to complex optimization issues.

Mathematical model of SGO: It consists of multiple components that regulate the SGO behavior when optimizing the solutions. A population of potential solutions is generated during the initialization phase. Two categories are created from a list of potential solutions like offensive players and defensive players. Based on fitness values, the attacking players desire to outperform the defensive players. Using a random movement approach, the offensive players push the defensive players to start a fight.

Each player's Winning State (WS) is established by evaluating the objective function. If the offensive player's WS is higher than the defensive players, then the offensive player is represented as the winner. Based on the results of the fights, the players' position vectors are updated.

The mathematical function of the solution F_q^p is expressed in Eq. (6).

$$F_q^p = F_{q,mn}^p + K_r \cdot \left(F_{q,mx}^p - F_{q,mn}^p\right) \begin{cases} q = 1,2,3...G \\ p = 1,2,3...V \end{cases} \quad (6)$$

Here, the total number of players is indicated as G, F_q^p is the p^{th} decision variable for evaluating the initial candidate, and K_r is the random variable. The terms $F_{q,mx}^p$ and $F_{q,mn}^p$ are the upper and lower boundaries of the q^{th} variable.

In the SGO algorithm, both the offensive F^{ofn} and defensive F^{dfn} player groups are designed to have an equal number of players. The dynamic and competitive aspect of the optimization process is enhanced by this equilibrium, which promotes equal and competitive exchanges between the two parties. The offensive and defensive players are statistically expressed in Eq. (7) and Eq. (8).

$$F^{ofn} = \begin{bmatrix} F_1^{ofn} \\ F_2^{ofn} \\ \vdots \\ F_G^{ofn} \end{bmatrix} \quad (7)$$

$$F^{dfn} = \begin{bmatrix} F_1^{dfn} \\ F_2^{dfn} \\ \vdots \\ F_G^{dfn} \end{bmatrix} \quad (8)$$

The division of solution candidates into offensive and defensive players in SGO raises a competitive environment. Through fitness assessments and exchanges with its rivals, players seek to improve their positions, which reflect an efficient and dynamic optimization process. The mathematical form of the defense group H_{dfn} is specified in Eq. (9).

$$H_{dfn} = \frac{\sum_{q=1}^{G} F_p^{dfn}}{G} \; q = 1,2,3...G \quad (9)$$

$$F_q^{Nof} = \frac{F_q^{Nof} + K_{r1} \times H_{dfn} - K_{r2} \times F_{Kr3}^{dfn}}{2} \; q = 1,2,3..B \quad (10)$$

Here, the term F_q^{Nof} is the q^{th} offensive player. The terms K_{r1} and K_{r2} are the random variable vary in the range of $[0,1]$. The objective function assessment is carried out using the fighting strategy to ascertain each player's WS. The fitness values derived from the objective function evaluation are used to determine the WS of each player. This evaluation impacts the SGO algorithm's position-updating process and assists in evaluating each player's success rate. The successful offensive player based on their fitness value is chosen to be part of the Successful Offensive Group (SOG).

$$S_g = \frac{\sum_{q=1}^{r} F_q^{Sf}}{r} \; q = 1,2,.3...r \quad (11)$$

$$F_q^{Nof2} = F_q^{Nof1} + K_{r1} \times S_g - K_{r2} \times Df \quad q = 1,2,3..B \quad (12)$$

The term r is the WS of the defense player, and F_q^{Nof2} is the new position of q^{th} player. All of the offensive participants in the optimization procedure are part of the offensive group. These players are responsible for making planned moves and decisions to improve their positions and outperform the defensive players. The mathematical form of the offensive group is expressed in Eq. (13).

$$O_g = \frac{\sum_{q=1}^{r} F_q^{df}}{v} \; q = 1,2,3...v \quad (13)$$

$$F_q^{df2} = F_q^{df} + K_{r1} \times O_g - K_{r2} \times F_q^{df} \quad q = 1,2,3..B \quad (14)$$

Finally, successful offensive players with higher WS than defensive players joined SOG. Offensive players in the SOG move toward successful defensive players to cross the bridge, while defensive players in the SDG approach, the crowd of offensive players and prepare offensive players for another fight. The pseudocode and flowchart of MF-SGO is provided in Algorithm 1 and Fig. 6.

Algorithm 1: Proposed MF-SGO			
Allocate the problem variables			
The maximum iteration and entire count of the population are initialized			
While $F_p < G_{\max}$			
Evaluate the fitness value			
A random variable K_r is upgraded in Eq. (5) based on the modified concept provided in Eq. (1)			
For $M_p = 1\ \ to\ G_{\max}$			
	For $F_q^p = 1\ \ to\ M_p$		
	The p^{th} offensive player moves toward the crowd using Eq. (9)		
	The winning stage is determined using Eq. (10)		
		If $F_G^{ofn} \le F_G^{dfn}$	
			The p^{th} best offensive player is move towards the crowd using Eq. (11)
			The p^{th} player joins SOG using Eq. (12)
		else $F_G^{ofn} > F_G^{dfn}$	
			The p^{th} best defensive player is move towards the crowd using Eq. (13)
			The p^{th} player joins to SDG using Eq. (14)
		End If	
	End For		
End For			
End While			
Obtain the best winning state			

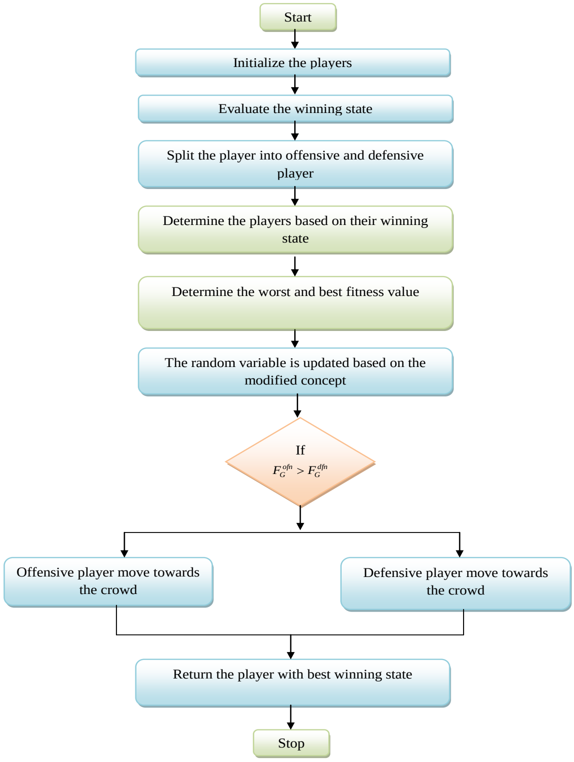


Fig. 6. Flowchart of proposed MF-SGO

6. Results and Discussion

A. Experimental analysis

The experimental analysis of depression classification involves assessing the performance and effectiveness of classification models in identifying persons with depression using diverse data sources, which was implemented in Python software. This experimental study often utilized structured methods like "Residual Network (ResNet) [27], Long Short-Term Memory (LSTM) [28], Visual Geometry Group (VGG16) [29], and MEANet [30]" for evaluating the model dependability and generalizability. The optimization algorithms like "Osprey Optimization Algorithm (OOA) [31], Tuna Swarm Optimization (TSO) [32], Cuttlefish Optimization (CO) [33], and Squid Game Optimizer (SGO) [26]" were chosen for training and validation to ensure the model reliability. The chosen models were trained on a subset of the dataset and confirmed on a separate validation set with a "number of populations as 10, chromosome length as 3, and maximum iteration as 50" to determine its efficacy. Cross-validation, hyperparameter tuning, and model optimization are used to boost the model's accuracy and generalizability.

B. Cost function analysis

Convergence analysis in the depression classification model is the analysis of optimization algorithm proceeds toward the optimal solution and the graphical representation, which is illustrated in Fig. 6. It determines the designed model over different iterations. Each algorithm iteratively updates the model parameters to minimize a predefined loss function. In analyzing the depression classification model, convergence speed is critical for determining how quickly the model learns from the data and converges to an ideal solution. Faster convergence rates generate more efficient learning. The cost function of MF-SGO-MEANet is enhanced with 87.17% than OOA-MEANet, 86.8% than TSO-MEANet, 66.6% than CO-MEANet, and 64.2% than SGO-MEANet at 10th iteration. Thus, cost function analysis proved that the training features of the depression classification model optimize the convergence process, and verified that the model achieves a precise outcome for identifying persons with depression.

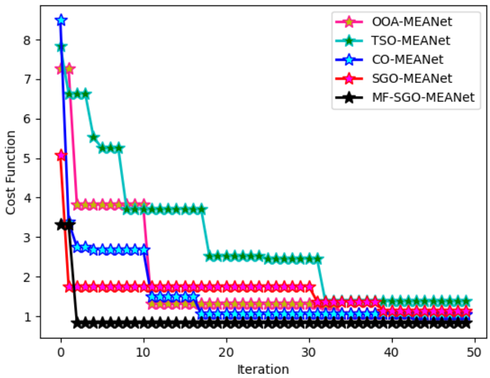
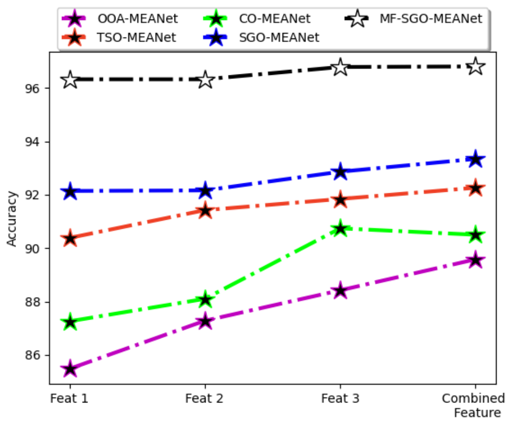


Fig. 7. Cost function analysis of the proposed depression classification model

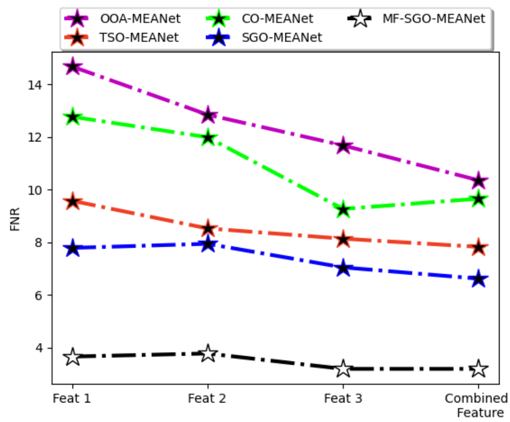
C. Performance analysis of the proposed model based on feature sets

Feature performance analysis using several classifiers involves evaluating the effectiveness of different features in distinguishing individuals with depression and those without depression. The graphical representations of feature analysis based on statistical performance like "Accuracy, FNR, FPR, NPV and precision" are illustrated in Fig. 7. The precision rate of feature set 3 is enhanced to 98.1% than other feature sets 1 and 2. Feature-based analysis helps to gain insights into the model decision-making process and recognize key predictors of depression. For feature set 1, the accuracy of MF-SGO-MEANet is boosted than existing models. Researchers analyze the utility of depression classification models, validate their performance, and involved to the creation of an accurate and reliable scheme for identifying persons at risk of depression by employing a systematic and rigorous feature analysis approach.

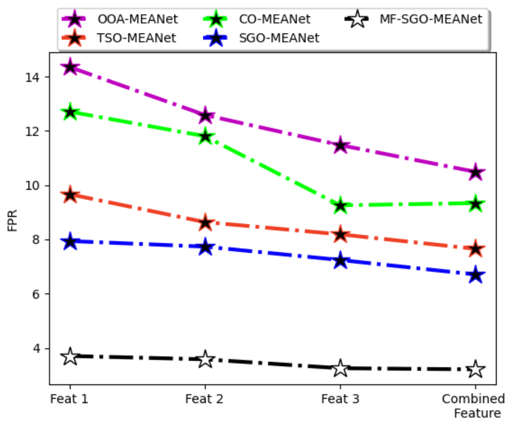
Algorithm comparisons


OOA-MEANet
TSO-MEANet
CO-MEANet
SGO-MEANet
MF-SGO-MEANet
Accuracy
Feat 1
Feat 2
Feat 3
Combined Feature

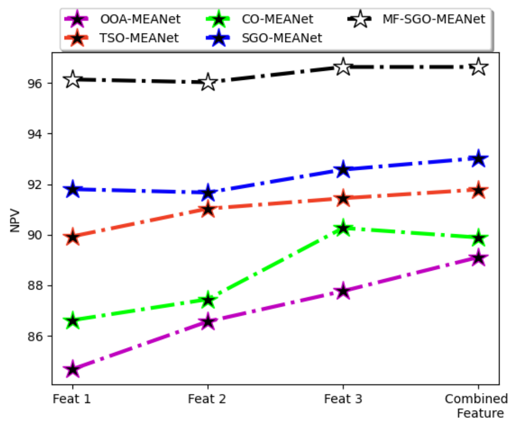
(a)


OOA-MEANet
TSO-MEANet
CO-MEANet
SGO-MEANet
MF-SGO-MEANet
FNR
Feat 1
Feat 2
Feat 3
Combined Feature

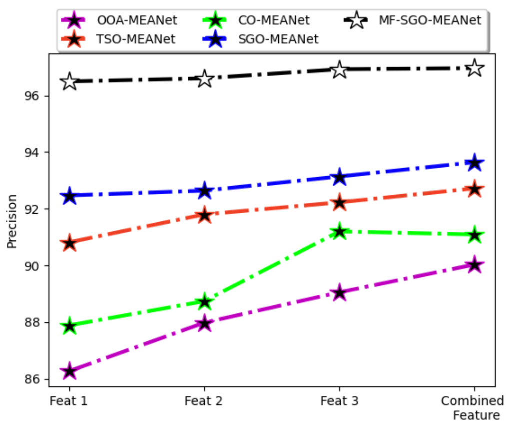
(b)


OOA-MEANet
TSO-MEANet
CO-MEANet
SGO-MEANet
MF-SGO-MEANet
FPR
Feat 1
Feat 2
Feat 3
Combined Feature

(c)


OOA-MEANet
TSO-MEANet
CO-MEANet
SGO-MEANet
MF-SGO-MEANet
NPV
Feat 1
Feat 2
Feat 3
Combined Feature

(d)


OOA-MEANet
TSO-MEANet
CO-MEANet
SGO-MEANet
MF-SGO-MEANet
Precision
Feat 1
Feat 2
Feat 3
Combined Feature

(e)

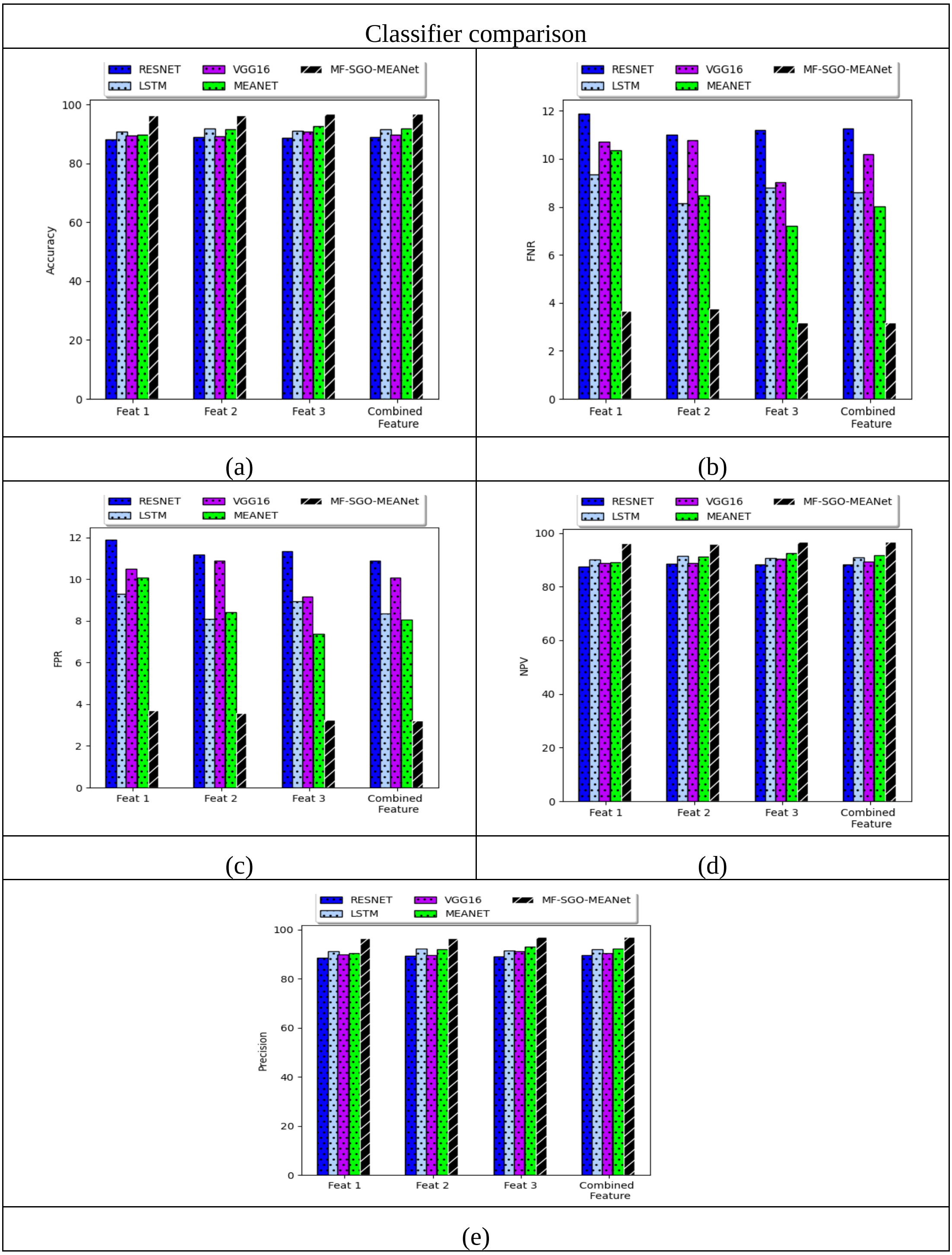
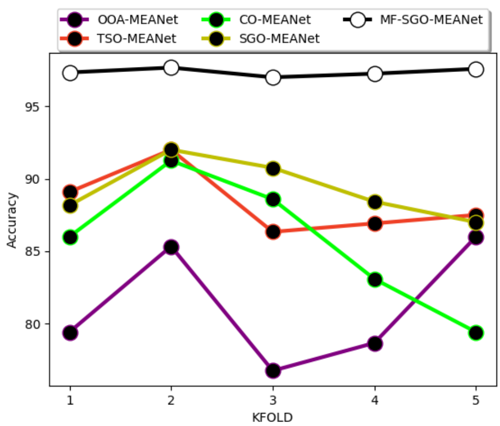


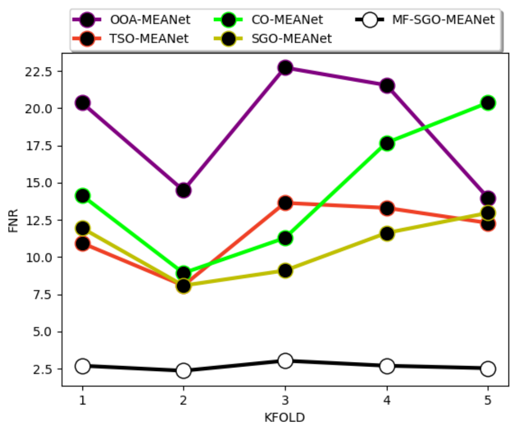
Fig. 8. Performance analysis of the proposed depression classification model based on feature sets regarding (a) Accuracy, (b) FNR, (c) FPR, (d) NPV, and (e) Precision

D. K-fold cross validation of the proposed model

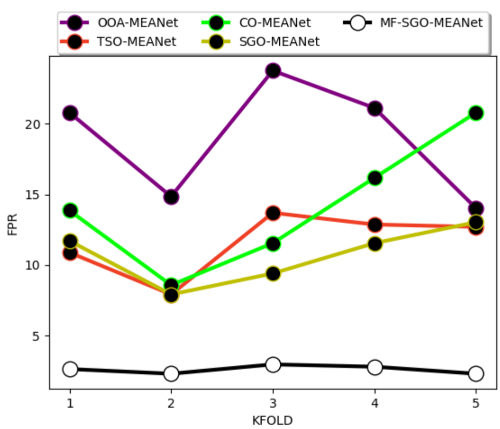
In the performance analysis of depression classification model using traditional classifiers and algorithms, K-fold cross-validation is applied to assess the reliability of the designed model and to evaluate the effectiveness of different features. The graphical analysis of K-fold variation among algorithm and classifier comparison for the performance metrics like "Accuracy, FNR, FPR, NPV and precision" are illustrated in Fig. 8. The overall model performance is assessed by aggregating the performance metric across all k-folds to ensure the robustness of the model. At 3rd K-fold value, the accuracy of the MF-SGO-MEANet is boosted with 8.8% than ResNet, 15.2% than LSTM, 22.5% than VGG16, and 3.15% than MEANet. Thus, from this analysis, the reliability of different classifiers using K-fold cross validation is assessed and the best classifier is chosen for having stable and reliable performance in terms of depression classification. Assess the bias and variance of the designed model across different K-folds illustrates that the proposed model greatly reduces the overfitting issues. Thus, this model generalized well to unseen data and captures the underlying patterns related to depression.

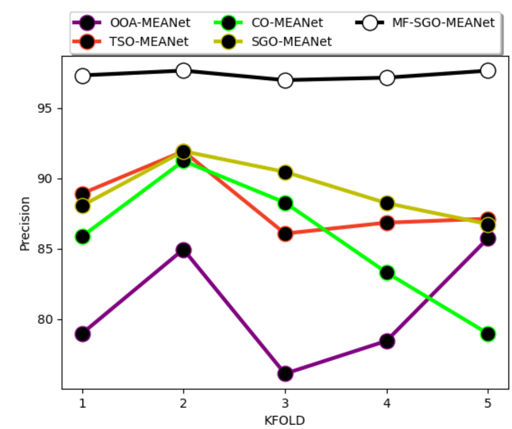
Algorithm comparisons



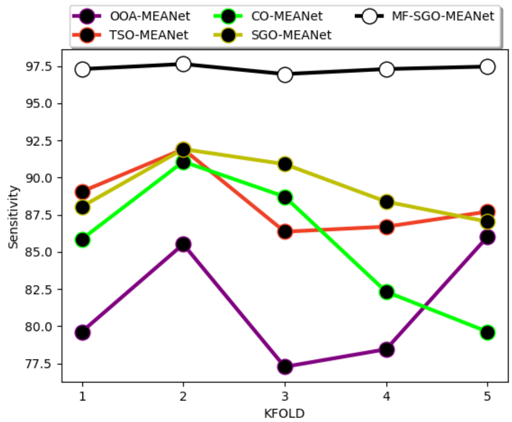


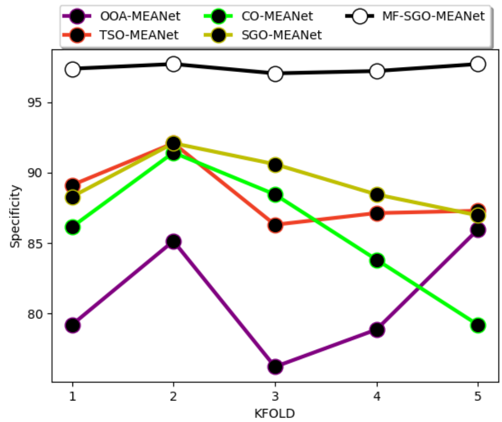
(a) (b)





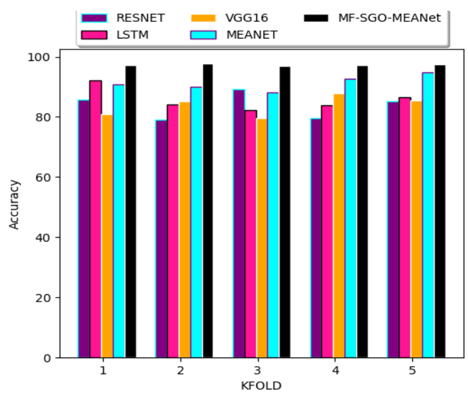
(c) (d)

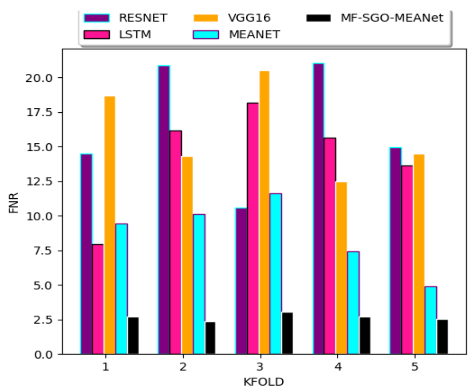




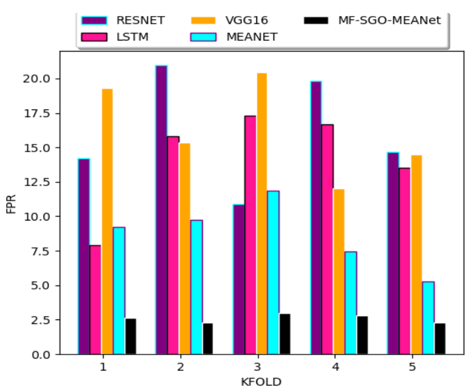
(e) (f)

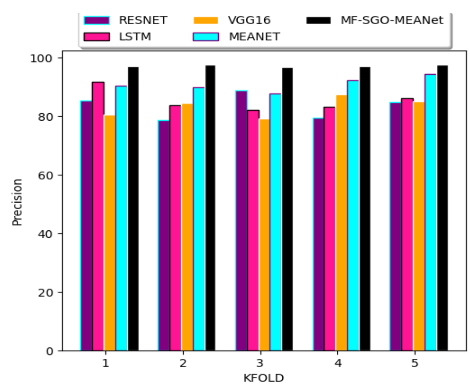
Classifier comparison



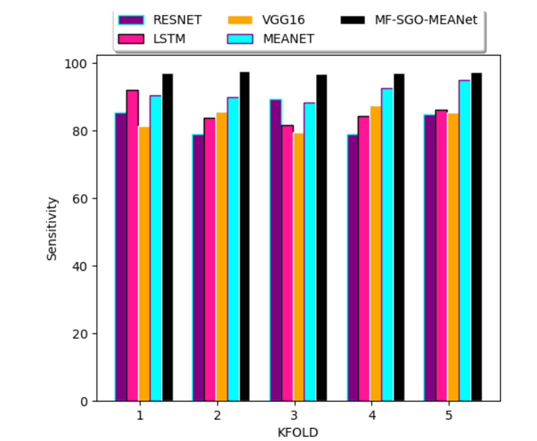


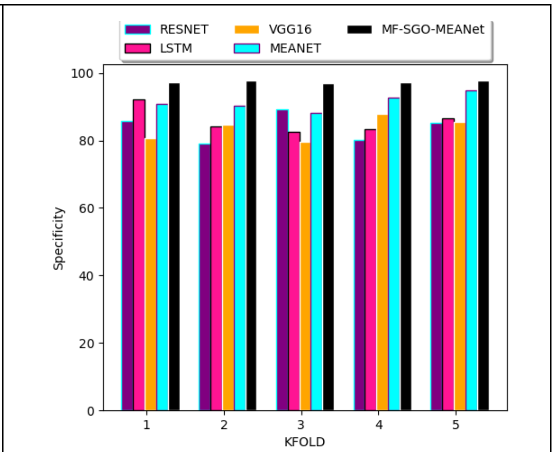
(a) (b)





(c) (d)





(e) (f)

Fig. 9. K-fold cross validation of proposed depression classification model among both classifiers and algorithms regarding (a) Accuracy, (b) FNR, (c) FPR, (d) precision, (e) sensitivity and (f) specificity

E. Statistical analysis of the proposed model

Statistical analysis plays an essential role in depression classification tasks. Different statistical measures like "best, worst, mean, median, and standard deviation" are used to compute the relevant features for depression classification. Statistical tests are conducted to determine if the classification errors are appreciably different between depression classes. Based on these statistical analyses, the mean value of MF-SGO-MEANet is enhanced with 51.6% than OOA-MEANet, 68.0% than TSO-MEANet, 41.8% than CO-MEANet, and 42.8% than SGO-MEANet. Interpret the statistical analysis findings in the context of depression classification, highlighting the key features and their impact on the classification outcome. By employing statistical analysis algorithms in depression classification tasks, researchers effectively identify important features and assess stability capabilities about the relationships between features and depression status.

TABLE II. STATISTICAL ANALYSIS OF THE PROPOSED MODEL AMONG DIFFERENT ALGORITHMS

TERMS	OOA-MEANet [31]	TSO-MEANet [32]	CO-MEANet [33]	SGO-MEANet [26]	MF-SGO-MEANet
Best	1.076506	1.382443	1.051719	1.143315	0.832288
Worst	7.261131	7.839013	8.492802	5.079839	3.336404
Mean	1.927181	2.921092	1.604872	1.630611	0.932453
Median	1.314017	2.493987	1.060504	1.763191	0.832288
Standard Deviation	1.480475	1.675952	1.195897	0.558037	0.490704

F. Extracted feature sets analysis

Feature performance analysis using traditional classifiers involves evaluating the success rate of different features in distinguishing between individuals with depression using well-established conventional techniques and algorithms. The numerical evaluations of feature sets are provided in Table III. Here, the relevance of features are evaluated based on statistical measures like “accuracy, precision, FPR, FNR, and NPV”. Feature selection is an essential step in building a depression categorization model. The reliability of this designed model is boosted by relevant feature selection. Most of the applicable feature is combined together to boost the reliability of model compared to individual features. This analysis helps in identifying relevant effects among features.

TABLE III. EXTRACTED FEATURE SETS ANALYSIS OF PROPOSED MODEL AMONG DIFFERENT ALGORITHMS AND TECHNIQUES

Algorithm Comparisons					
TERMS	OOA-MEANet [31]	TSO-MEANet [32]	CO-MEANet [33]	SGO-MEANet [26]	MF-SGO-MEANet
Accuracy	89.2	90.42	90.68	93.56	96.76
Precision	89.15566	90.32774	90.7014	93.51741	96.71869
FPR	10.82701	9.668398	9.268877	6.472233	3.276069
FNR	10.77293	9.49139	9.371245	6.407689	3.203845
NPV	89.2443	90.51241	90.65868	93.60256	96.80128
Technical Comparisons					
TERMS	RESNET [27]	LSTM [28]	VGG16 [29]	MEANET [30]	MF-SGO-MEANet
Accuracy	87.8	91.4	90.58	92.94	96.76
Precision	87.72491	91.38967	90.52	92.94872	96.71869
FPR	12.26528	8.589692	9.468638	7.031562	3.276069
FNR	12.13456	8.610332	9.371245	7.088506	3.203845
NPV	87.87515	91.41031	90.64	92.93131	96.80128

G. Batch size-based numerical analysis

In the depression recognition model using deep learning techniques and algorithms, the analysis of batch size plays very useful role for training and optimization process. The numerical analyses of batch size variation are provided in Table IV. Batch size refers to the number of samples processed by the model in each iteration during training. It influences the speed of training, memory usage, and convergence of the model. The batch counts start from 100 and gradually increase to observe the effect on training dynamics and model accuracy. Small batch counts during training lead to noisy gradients and slow convergence. However, the large batch count during training utilizes parallel processing efficiently and requires less memory improves convergence speed, and enhances the overall success rate of the classification model for accurate detection of depression symptoms.

TABLE IV. BATCH SIZE ANALYSIS OF THE PROPOSED MODEL AMONG DIFFERENT ALGORITHMS AND TECHNIQUES

Algorithm Comparisons					
Batch size	OOA-MEANet [31]	TSO-MEANet [32]	CO-MEANet [33]	SGO-MEANet [26]	MF-SGO-MEANet
100	78.41666667	93.25	89.33333333	93.08333333	97.25
200	77.91666667	86.41666667	80.75	92.66666667	96.08333333
300	82.58333333	85.25	91.	89.	95.58333333
400	77.83333333	86.58333333	84.75	94.08333333	97.91666667
500	73.	85.58333333	80.83333333	91.66666667	95.83333333

Technical Comparisons					
	RESNET [27]	LSTM [28]	VGG16 [29]	MEANET [30]	MF-SGO-MEANet
100	73.91666667	89.75	77.16666667	85.16666667	97.25
200	87.	83.	81.75	94.	96.08333333
300	87.41666667	87.75	82.	94.08333333	95.58333333
400	80.75	87.5	85.41666667	91.08333333	97.91666667
500	82.83333333	88.5	89.41666667	93.83333333	95.83333333

7. Conclusion

An effective depression classification framework was developed to address the rising prevalence of depression. It is a successful method for identifying individuals with depression using text data, EEG signals, and video collected from different datasets. The relevant features from multi-modal inputs were collected and based on these pertinent features, classification were performed. Different modalities give flattering information, which raises the model ability to recognize subtle and diverse symptoms of depression. Finally, the MEANet model was designed to perform depression classification based on the relevant features. The success rate of the designed model was upgraded by optimizing the variable from MEANet using MF-SGO during the training and optimization process. Based on the extracted features, the accuracy of the designed model was boosted with 89.2% than OOA-MEANet, 90.4% than TSO-MEANet, 90.6% than CO-MEANet, and 93.5% than SGO-MEANet. Thus, the designed model is trained to be resistant to noise and unpredictability in data, which is especially useful when dealing with real-world data for the identification of depressed persons. Combining transfer learning and deep computing approaches for extracting hierarchical characteristics from EEG signals will improve the model scalability and accuracy on a wide range of datasets. Incorporating multimodal data sources, such as EEG signals together with other physiological variables, will enhance the model's diagnostic ability and provide deep neural information about the cause of depression. Integrating many data modalities will improve the model's accuracy and durability in recognizing and classifying depressed patients.

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