Brain and Heart Rate Variability Patterns Recognition for Depression Classification of Mental Health Disorder

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***Abstract*—Depression is common and dangerous if untreated. We must detect depression patterns early and accurately to provide timely interventions and assistance. We present a novel depression prediction method (depressive-deep), which combines preprocess brain electroencephalogram (EEG) and ECG-based heart-rate variability (HRV) signals into a 2D scalogram. Later, we extracted features from 2D scalogram images using a fine-tuned MobileNetV2 deep learning (DL) architecture. We integrated an AdaBoost ensemble learning algorithm to improve the model's performance. Our study suggested ensemble learning can accurately predict asymmetric and symmetric depression patterns from multimodal signals such as EEG and ECG. These patterns include major depressive state (MDS), cognitive and emotional arousal (CEA), mood disorder patterns (MDPs), mood and emotional regulation (MER), and stress and emotional dysregulation (SED). To develop this depressive-deep model, we have performed a pre-trained strategy on two publicly available datasets, MODMA and SWEEL-KW. The sensitivity (SE), specificity (SP), accuracy (ACC), F1-score, precision (P), Matthew's correlation coefficient (MCC), and area under the curve (AUC) have been analyzed to determine the best depression prediction model. Moreover, we used wearable devices over the Internet of Medical Things (IoMT) to extract signals and check the depressive-deep system's generalizability. To ensure model robustness, we use several assessment criteria, including cross-validation. The depressive-deep and feature extraction strategies outperformed compared to the other methods in depression prediction, obtaining an ACC of 0.96, IOTSE of 0.98, SP of 0.95, P of 0.95, F1-score of 0.96, and MCC of 0.96. The main findings suggest that using 2D scalogram and depressive-deep (fine-tuning of MobileNet2 + AdaBoost) algorithms outperform them in detecting early depression, improving mental health diagnosis and treatment.**

Keywords*—*Mental health disorder; depression patterns; electroencephalogram; heart rate variability; deep learning; mobilenet; behavioral analysis; internet of medical things

I. Introduction

Mental depression is a global health issue that affects people of all ages and genders [1]. Especially during the COVID-19 epidemic, stress and anxiety have widely affected the health of humans. Early depression pattern detection can improve treatment outcomes, prevent suicidal tendencies, and improve mental health care [2, 3]. Traditional depression diagnosis uses clinical examinations, questionnaires, and interviews [4]. While these methods are useful, they are often subjective and constrained by healthcare providers' biases and expertise [5]. Technology and machine learning have shown promise in improving diagnostic procedures in recent years [6]. Most importantly, based on current data, CAD systems can forecast patient health outcomes [7]. AI has transformed pathology identification using these data. Previous research has proposed EEG and HRV models for early neurological disease identification [8].

Enhanced alpha power, decreased beta power, frontal asymmetry, and diminished connectivity are EEG features [9]. HRV patterns show reduced HRV, increased sympathetic activity, and decreased parasympathetic activity. Some elements may not apply to EEG and ECG patterns since they are distinct [10]. Fig. 1 visualizes EEG and ECG-based HRV signals. Our analysis reveals specific patterns like MDS with marked asymmetry in brain wave activities, while CEA exhibits more symmetrical features. The model discerns depression states using both symmetrical and asymmetrical signal patterns as biomarkers for accurate diagnosis.

EEG patterns (alpha and beta power, frontal asymmetry, and connectivity) indicate brain activity linked to depression. Higher frontal alpha power suggests lower brain activity, while beta power indicates tension or worry. Frontal asymmetry relates to affective and motivational dysregulation. Depressed individuals may show altered brain connectivity. HRV patterns reflect the stress-relaxation balance, with depression causing increased sympathetic or decreased parasympathetic activity. These representations go beyond 'cosine signals' to depict depression's physiological alterations and biological relationships.

EEG and ECG are multimodal data valuable for mental health assessment. EEG non-invasively records brain activity, revealing cognitive and emotional processes [11]. HRV measures autonomic nervous system activity and emotional modulation through heartbeat intervals. EEG and HRV are objective indicators for depressive patterns [12]. Mobile crowd sensors (MCSs) use mobile device sensors for data sharing and behavior tracking, essential for Internet of Medical Things (IoMT) applications. This study uses MCS to quantify symptoms and diagnose depression patterns from EEG and ECG-based signals, analyzing smartphone usage for behavioral insights.

TABLE I. COMPARISON STUDIES ON DETECTING DEPRESSION PATTERNS USING MACHINE LEARNING AND DEEP LEARNING TECHNIQUES, INCLUDING THE DATASET, ACCURACY, AND LIMITATIONS OF EACH APPROACH

Study	Methodology	Dataset	Accuracy (%)	Limitations
[22]	Machine Learning (Nonlinear Features + Logistic Regression)	EEG signals	90.00	Limited to EEG data, may not generalize widely.
[23]	Deep Learning (CNN + LSTM)	EEG signals	99.07 (Right) / 98.84 (Left)	Complex model, computationally intensive.
[24]	Ensemble Learning + Deep Learning (Power Spectral Density)	EEG data from emotional face stimuli task	89.02	Performance may vary with different features.
[25]	Machine Learning (SVM, LR, NB)	EEG-based functional connectivity	SVM: 98.00, LR: 91.70, NB: 93.60	Limited to functional connectivity features.
[26]	Deep Learning (CNN-LSTM)	EEG signals	99.12 (Right) / 97.66 (Left)	Computationally intensive, deep model.
[27]	Deep Learning (CNN)	EEG signals	93.50 (Left) / 96.00 (Right)	Focus on specific hemisphere EEG signals.
[28]	Deep Learning (DWSN)	EEG signals	GMC: 99.95, MODMA: 99.30	May require substantial computational resources.
[29]	Deep Learning (GCN + Attention)	EEG signals	92.87 / 83.17	May require significant training data.
[30]	Machine Learning (VMD + EEG Channel Selection)	EEG signals	Varies based on channel selection	Dependent on channel selection method.
[31]	Deep Learning (MFCC + CNN)	Audio Data (DAIC-WOZ, MODMA, RAVDESS)	Over 90%	Limited to audio-based depression detection.
[32]	Handcrafted Classification Model (TPTLP + KNN)	EEG signals	76.08 (Channel 1) / 83.96 (Top 13 Channels)	May not achieve as high accuracy as deep learning.
[33]	Machine Learning (CNN)	EEG signals	97.00	May not capture complex patterns in EEG data.
[34]	Machine Learning (Decision Tree, Random Forest, etc.)	EEG signals	98.13 (CNN + Band Power)	Limited to EEG data, may not generalize widely.
[35]	Deep Learning (Self-Attention + CNN)	EEG signals	91.06	May require substantial training data.

We combine deep and ensemble learning to predict depression using EEG and HRV data. The MobileNetV2 deep learning model analyzes 2D arrays, and AdaBoost ensemble learning improves predictive power. We aim to test EEG and ECG-based HRV as depression biomarkers, evaluate the model, and identify relevant features for accurate predictions. Our model is an auxiliary tool for mental health assessment and should complement healthcare experts' experience. This depressive-deep system transforms 1D multimodal signals into 2D scalograms using HRV and EEG datasets. After preprocessing, useful features are extracted by fine-tuning MobileNetV2, addressing the challenge of feature selection without overfitting.

The main contributions using fine-tuned MobileNetV2 and AdaBoost to recognize multiple depression patterns from HRV and EEG data are:

1) This work uses MobileNetV2, a lightweight deep learning model, and AdaBoost, an ensemble learning method.

2) This new approach improves depression pattern identification from multimodal ECG and EEG data by combining their capabilities into one 2D scalogram.

3) This research shows depression pattern prediction outperforms existing methods. The MobileNetV2 and AdaBoost models outperform earlier methods in mental health diagnosis, demonstrating the potential of sophisticated machine learning.

4) The model's potential for early depression diagnosis and treatment is highlighted. This strategy could improve mental health by monitoring and supporting depressed people via wearable gadgets or smartphone apps.

Our developed model is detailed in the subsequent article sections. In Section II, we described the literature review. Afterwards, the article begins with a full discussion of EEG and ECG signal preprocessing procedures to create 2D scalograms in Section III. Next, we present the MobileNetV2 deep learning model's design and fine-tuning, then integrate the AdaBoost ensemble learning method to improve prediction performance. The study presents MODMA and SWEEL-KW datasets in Section IV with assessment metrics for model accuracy, sensitivity, specificity, precision, F1-score, MCC, and AUC. We also address IoMT-based wearable device deployment to test the model's generalizability. Finally, we compare our technique to others and show that the depressive-deep model is better at early depression identification. Section V describes the discussion of this paper and finally, the paper concludes in Section VI.

II. LITERATURE REVIEW

The literature on depression diagnosis using ECG-based HRV and EEG data explores deep learning and ensemble learning in mental health diagnoses, highlighting research gaps and new methodologies. Depression has serious social and economic effects. Researchers have used HRV and EEG data to detect depression patterns. This section reviews experiments using MobileNetV2 and AdaBoost to analyze HRV and EEG data.

In study [13], a novel EEG-based depression detection method employs MobileNetV2 deep learning and SVM classifiers to analyze EEG spatial and temporal patterns. In study [14], HRV data predicts depression using AdaBoost, combining weak classifiers for reliable predictions. MobileNetV2's architecture in study [15] addresses deep learning on mobile devices with minimal complexity and improved performance. In study [16], HRV-based depression diagnosis using AdaBoost improves model performance and recognition accuracy. The literature shows increasing use of MobileNetV2 and AdaBoost for diagnosing depression from HRV and EEG data. These strategies could improve mental health diagnoses. More research is needed to address data availability, interpretability, and real-world applicability issues, enhancing depression detection technologies. Relevant papers on HRV and EEG data in machine learning include studies on model evaluation metrics like RMSE and MAE [17].

Sathyanarayana and Krishnan propose a hybrid deep learning model using CNNs and LSTM networks to assess EEG and HRV data [18]. Shi et al. use a brain-functional network-based EEG feature selection method for depression recognition [19]. This study examines nonlinear complexity in brain functional fMRI signals in schizophrenia [20], while Subhani et al. assess brain functional connectivity using deep learning with resting-state fMRI data [21]. Previous systems [22–27] using deep learning architectures like CNN and LSTM with 1D EEG signals recognized limited depression patterns. Sharma et al. (2024) proposed a Deep Wavelet Scattering Network (DWSN) for automated depression identification using EEG signals [28], achieving high accuracy. Zhang et al. (2024) used a graph convolution network with an attention mechanism for depression detection in public datasets [29].

Aljalal et al. (2024) detected minor cognitive impairment using variational mode decomposition and machine learning with few EEG channels [30]. Das and Naskar (2024) proposed an MFCC-CNN model for depression identification from audio signals, achieving over 90% accuracy [31]. Tasci et al. (2023) used cross-validation for identifying MDD with EEG signals [32]. Ksibi et al. (2023) employed CNN and machine learning for detecting depression patterns in EEG data [33]. Khadidos et al. (2023) used band power features for depression identification, achieving high accuracy with CNN models [34]. Xia et al. (2023) used an end-to-end deep learning model for EEG-based depression classification, achieving high accuracy [35]. These studies advance mental health diagnosis through various EEG signal processing methods and machine learning models. Table I compares these state-of-the-art studies.

III. Proposed Methodology

Fig. 1 displays the systematic flow diagram. This study used numerous essential phases. First, we obtained ECG-based HRV and EEG data from both depressed and non-depressed individuals using wearable heart rate monitors and specialist devices. We protected data privacy through ethical approval and informed permission. Preprocessing included HRV data normalization, artifact removal, and EEG data filtering and artifact removal. Next, we transform the preprocessed ECG and EEG data into 2D scalogram images. We fine-tuned MobileNetv2 to extract features from HRV dynamics and brain activity patterns. The suggested model architecture integrated MobileNetV2, a lightweight deep learning model, with AdaBoost ensemble learning. We assessed the model performance using cross-validation metrics such as accuracy, sensitivity, specificity, precision, F1-score, and AUC. SMOTE created synthetic depressed samples to correct the class imbalance. We used Python, scikit-learn, and TensorFlow for hyperparameter tuning and optimization. The study noted limitations like the short dataset and potential overfitting and advised caution when interpreting model results. The study used ECG-based HRV and EEG data and advanced machine learning to improve depression pattern recognition and mental health diagnoses.

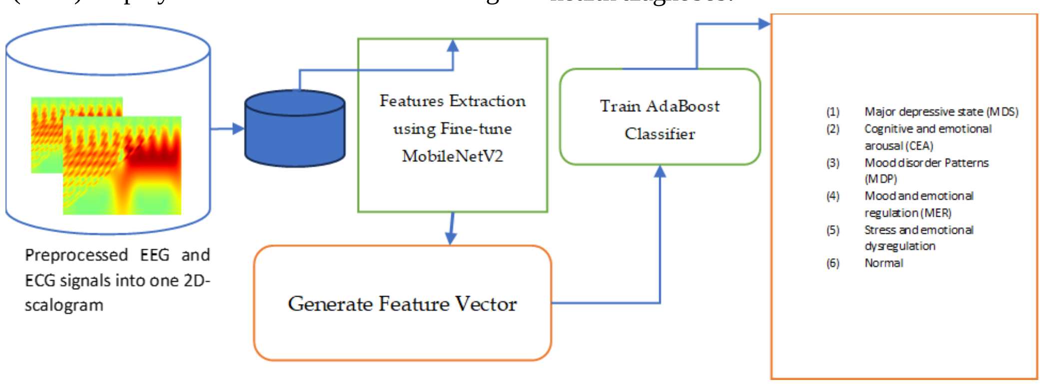


Fig. 1. A systematic flow diagram of the proposed system for detecting multiple depression patterns from EEG and HRV signals.

TABLE II. Data Description Captured from MODMA and SWELL-KW Datasets

Dataset	Properties	Values
MODMA [36]	Subjects with depression	30
	Channels	128
	Sampling rate (Hz)	1000
SWELL-KW [37]	Subjects	32
	Subjects with depression	25
	Male/female ratio	8/17
	ECG	6
	Sampling rate (Hz)	0.0 to 1000
Total	Number of Subjects	45

A. Data Acquisition

We collected heart rate variability (HRV) based on ECG and brain activities through EEG data from a diverse group of participants, which included individuals with different patterns of depression and those without depression. We obtained the HRV data using wearable heart rate monitors and captured the EEG data using a specialized electroencephalogram (EEG) device. The EEG [36] and ECG data [37] are available online. People commonly use a heart rate monitor or an electrocardiogram (ECG) device to capture HRV signals. These devices are non-invasive and can accurately measure variations in time intervals between successive heartbeats. The remaining paragraphs describe the details of the datasets in Table II.

EEG signal data utilized in this study are sourced from the MODMA dataset [36], a multi-modal open dataset designed for research on mental disorders. The dataset includes EEG data obtained from individuals wearing a conventional 128-electrode elastic cap or a newly developed wearable EEG collector with three electrodes, suitable for a broader application. Specifically, this investigation focuses on analyzing resting-state EEG signals collected from individuals equipped with the 128-channel cap. Inclusion criteria for participants in the MODMA dataset require them to be aged between 18 and 55, have normal or corrected-to-normal vision, and possess at least an elementary level of education. Some patients were diagnosed with major depressive disorder (MDD). Moreover, patients with MDD should not have used psychotropic drugs within the two weeks preceding data collection, and control group participants should have no history of mental illness in their families. To maintain sample integrity and enhance the generalizability of results, individuals with pre-existing mental illnesses, brain injuries, significant physical ailments, or severe suicidal tendencies were excluded from the MODMA dataset.

For MODMA and SWELL-KW signal average durations, our study used EEG- and ECG-based HRV data with 5 min sessions. This length is the same as resting-state EEG and short-term HRV methods. It gives us a balanced way to obtain useful physiological information about depressed states while still making sure the participants are comfortable. These 5 min sessions often capture a complete image of brain activity and heart rate variability, laying the groundwork for our depression-related pattern analysis without burdening subjects. Fig. 2 shows the visual representation of EEG and ECG-based HRVE signals.

B. Signal Preprocessing

Preprocessing steps on multimodal (EEG, ECG) signals is performed to remove noise and accurately extract depression patterns. EEG data are initially preprocessed for depression pattern analysis using a bandpass filter. This filter isolates frequency components linked to depression-related brain activity. A typical filter, the Butterworth bandpass filter, focuses on a specified frequency range, usually 1–30 Hz. This filtering stage reduces noise and highlights important frequencies. The EEG data are then used to determine connection characteristics. Coherence or phase synchronization analysis yields these traits. The outcome is a connection matrix, with each member representing EEG channel connectivity strength. These findings show complicated brain area relationships, which might help explain depression. EEG characteristics are normalized by the algorithm for uniformity and comparability. This step centers the data at zero mean and scales them to unit variance. The method standardizes the features by determining the mean and standard deviation for each feature over all EEG samples. Normalization removes biases and guarantees that all characteristics contribute equally to the analysis.

ECG signal preprocessing begins with data preparation for analysis. Depending on the dataset and needs, these processes may involve resampling HRV signals to a specified sampling frequency and applying low-pass filters to reduce noise and artifacts. Resampling synchronizes ECG and EEG data for useful analysis. After preparing ECG data, the system extracts depression-related HRV characteristics. Autonomic nervous system components like sympathetic and parasympathetic activity are routinely measured. These measurements are calculated for each ECG segment using feature extraction. These traits reveal depression's physiological elements. The preprocessed EEG and ECG characteristics are saved separately for analysis in the final stage, as shown in Fig. 3. These characteristics are now ready for machine learning or statistical analysis to discover depressive tendencies. We can construct models or conduct statistical studies using these processed characteristics to better understand depression patterns and enhance diagnosis and therapy.

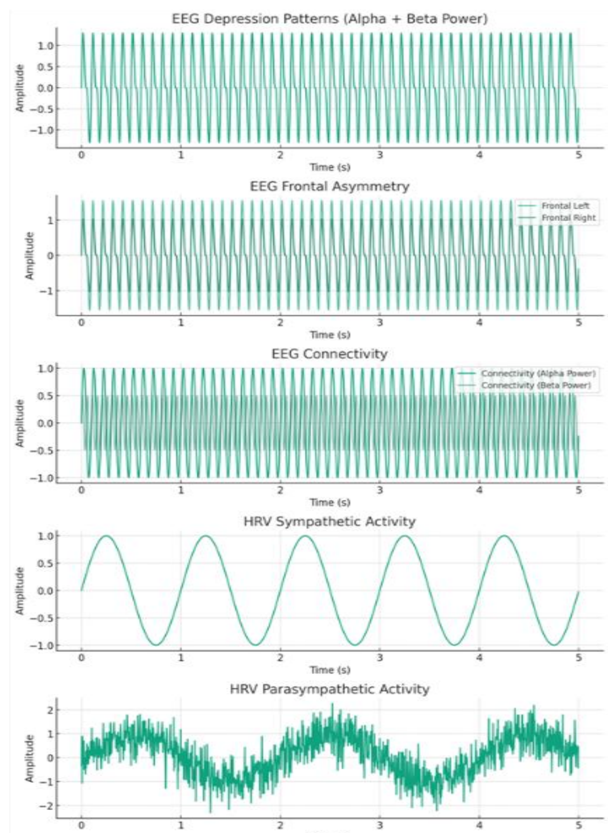


Fig. 2. A sample EEG- and ECG-based HRV multimodal signals from MODMA and SWELL-KW datasets.

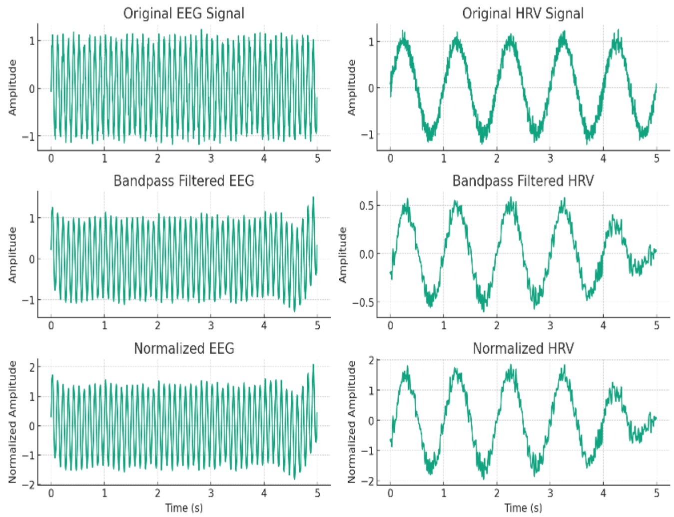


Fig. 3. A visualized diagram of EEG- and ECG-based HRV original and preprocess signals.

C. Signal Transformations

This modified algorithm takes preprocessed EEG and ECG signals as input and generates 2D scalogram-like images by applying continuous wavelet transform (CWT) to both signals, as shown in Fig. 4. It then combines the resulting images to form a single scalogram-like depression pattern. The following paragraphs explain the process. The first stage is preprocessing EEG and ECG signals. This preprocessing involves noise filtering, signal normalization, and segmenting continuous data into digestible parts. This cleans and standardizes signals for analysis. We separate the signals into time-window-sized parts after preprocessing. Zero-padding standardizes these segments' lengths. Standardization is essential for fair segment comparison and analysis. The next stage applies the continuous wavelet transform to each EEG and ECG segment. The CWT uses a scaled and shifted dynamic window (the main wavelet) to assess these segments' frequency content over time. This approach is ideal for EEG and ECG signals because it can analyze high and low frequencies with acceptable resolution and capture the temporal evolution of multiple frequency bands. The CWT produces EEG and ECG scalograms.

Scalograms are 2D image patterns that show a signal's frequency components across time. The intensity of the image corresponds to the amplitude of these components at different frequencies and periods. Combining EEG and ECG scalograms creates a single, complete pattern in a 2D image. This image shows probable depression patterns by combining EEG and ECG data. We normalize the combined scalogram pictures for size, brightness, and contrast to facilitate comparison and study. This standardization lets scalogram patterns be seen, algorithmically evaluated, and compared, as shown in Fig. 4. We divide EEG and ECG data into small patches. Each component represents a short data period. We add zeros to short bits to make them all the same size. This guarantees fair comparisons of all components. Over time, we examine how frequencies like high and low pitches change in each piece of data. This reveals depressive tendencies. Each data point is transformed into a "scalogram" using the CWT transform. We mix EEG and HRV scalograms to create one image. This graphic depicts depression's effects on brain activity and heart rate. For simple comparison, we keep our photographs the same brightness and blackness. After performing this for all our data, we have 2D depression pattern images. Each 2D image illustrates patterns from our EEG and ECG data that might help us understand depression. Preprocessed EEG and HRV data are converted into 2D images for image.

The continuous wavelet transform (CWT) uses a dynamic window called the main wavelet to distinguish it from the short-time Fourier transform (STFT). This wavelet is scaled and shifted during transformation, providing large low-frequency and short high-frequency time intervals. The STFT uses constant window sizes, whereas the CWT can adapt to different window sizes to evaluate both high- and low-frequency components in a time series [34]. CWT is ideal for EEG analysis due to its versatility. To maximize resolution, the approach uses smaller scales for high frequencies and bigger scales for low frequencies. In practice, CWT or STFT depends on signal properties and analytic aims. The CWT advantages include great flexibility, accurate frequency localization, and thorough time-frequency information. STFT is more economical and may be suited for simpler applications where fine-grained time-frequency analysis is not necessary. The CWT transform technique is calculated by Eq. (1) as:

$$\mathrm{W}_x(\mathrm{s},\tau) = \frac{1}{\sqrt{s}} \int_{-\infty}^{\infty} x(t)\, \psi' \left(\frac{\mathrm{t}-\tau}{s}\right) dt \qquad (1)$$

The continuous Wavelet Transform (CWT) is a technique that creates scalograms from EEG and ECG data. It analyzes data, typically a continuous-time signal, using multiple wavelet expansions and time offsets, notably the Morlet Continuous Wavelet. The resulting CWT scalograms provide an interpretable view of the local time-frequency energy density in the signal. Each signal segment is transformed into a scalogram picture, making the data more accessible for examination. Our work involved the production of 500 photos, 100 for each segment, demonstrating the interpretability of the analysis. These scalogram pictures, with their detailed frequency components, unveil the temporal and frequency properties of blood volume changes throughout cardiac cycles, engaging the viewer in the analysis process. Finally, the example scalogram pictures of three individuals, possibly demonstrating the post-CWT transformation data, may reveal signal differences or distinctive characteristics.

A major step in developing scalogram-based images was using the Morlet wavelet as a continuous wavelet transform (CWT). Next, the algorithm requires a list of pre-processed EEG and ECG signal segments representing data time intervals. Each segment has values indicating signal amplitudes at discrete times. The approach initializes an empty 2D NumPy array named "image_matrix". The scalogram information for each signal segment will be stored in this array, with rows representing segments and columns indicating time or frequency bins. Steps taken by the algorithm for each EEG and ECG segment in the input list: (1) Based on segment duration and sampling rate, calculate segment data points. (2) To guarantee consistency, pad the segment with zeros if it is shorter than required. (3) Calculate the segment scalogram using CWT. The transformation depends on the Morelet wavelet type. (4) Use the scalogram absolute value to measure frequency component magnitude. (5) Resize the scalogram to fit the picture length provided by desired_length. This method creates a 2D scalogram as shown in Fig. 4 to show the frequency content of several signal segments. Time-varying frequency components of data can be analyzed. The overall algorithm steps are shown in Algorithm 1.

Algorithm 1: Generating 2-D scalogram image from Preprocessed EEG and ECG signals

Input: x: Preprocessed EEG and ECG signals
Output: $image_{spectrogram}$: frequency content of EEG and ECG signal segments
[Initialize Parameters]
desired_length = 256×256
segment_duration = 5s
sampling_rate = 250 Hz
wavelet = 'Morlet'
Function generate-scalogram (N_{eeg}, N_{hrv}):
$image_{scalogram} = padding$(desired_length ,0);
For each $segment(eeg, hrv)$ **in zip(**N_{eeg}, N_{hrv}**) do**
D = $Calculate\_datapoints(segment\_duration * sampling\_rate)$;
eeg −scalogram, frequencies = $CWT(eeg\_segment, scales, wavelets)$;
hrv −scalogram, frequencies = $CWT(hrv\_segment, scales, wavelets)$;
eeg − r = $Resize(abs_{eeg} - scalogram, desired\_length)$;
hrv − r = $Resize(abs_{hrv} - scalogram, desired\_length)$;
$image_{scalogram} = image_{scalogram} +$ eeg − r + hrv − r
end
Return ($image_{scalogram}$);
End of algorithm

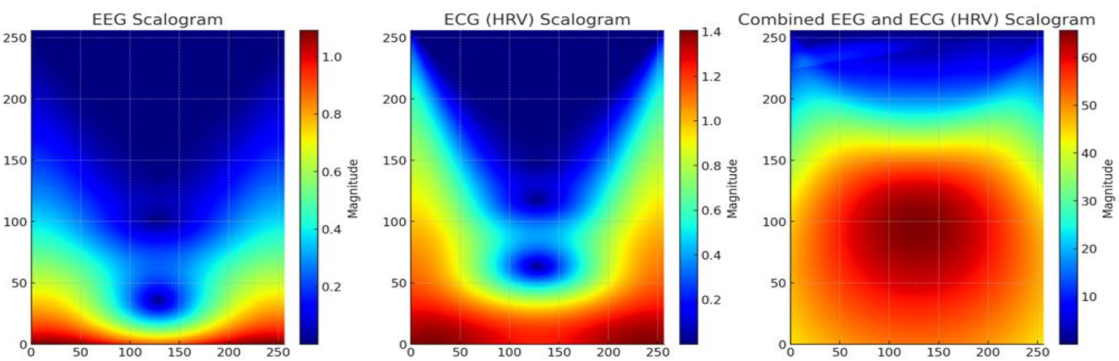


Fig. 4. Scalograms visualize EEG and ECG signals, where figure (a) shows the preprocessed EEG scalogram, (b) presents the ECG scalogram, and then figure (c) combines 2D scalogram representing depression patterns.

D. Features Extraction

This table lists the MobileNetV2 and AdaBoost hyperparameters needed to train and optimize the models for early depression diagnosis using EEG- and ECG-based HRV inputs. The dataset, challenge, and computational resources for the research will determine these hyperparameter values. Tuning these hyperparameters can greatly affect model performance and generalizability. In our approach, we use scalograms extracted from EEG- and ECG-based HRV to input a fine-tuned MobileNetV2 model for depression pattern recognition. Freezing several basic MobileNetV2 layers, adding a classification layer, tweaking hyperparameters like learning rate and dropout rate, and training on the fine-tuning dataset are carried out by the algorithms. This method refines hyperparameters until performance is attained. The depression pattern detection model is generated by testing the fine-tuned MobileNetV2 model on a test set.

Specifically optimized for mobile devices, MobileNetV2 is a CNN architecture with a unique structure as shown in Fig. 5 that establishes connections between bottleneck layers. Moreover, it employs deep folds in the intermediate expansion layer to extract nonlinear features effectively. The MobileNetV2 architecture comprises 32 layers of initial convolution followed by 19 bottleneck layers. In this research, we introduce a customized MobileNetV2 design incorporating two innovative fine-tuning strategies for the identification of 2D depression images.

MobileNetV2 has various benefits over other deep learning systems. It thrives on tiny datasets with difficult training and substantial overfitting risk. MobileNetV2 reduces overfitting, making it a good visual classification algorithm. It optimizes memory utilization and reduces errors, making it fast and efficient. The MobileNetV2 architecture speeds transaction execution, facilitating testing and parameter tuning. The transfer learning method of fine-tuning uses pre-trained CNN models to classify new tasks efficiently. While constructing a CNN model from the start is time-consuming and computationally costly, fine-tuning is an efficient option. Main strategies for using pre-trained transfer learning models include feature extraction, categorization, and fine-tuning. This method uses the pre-trained CNN model to extract features. New layers tailored for the destination dataset's classes replace the model's final, completely linked layers. The pre-trained model collects key information and classifies additional layers. Fine-tuning is achieved by changing and training selected top layers of the pre-trained CNN model and adding classifier layers. This method lets the model tailor its high-level feature representations to the task. Later layers in the model are more specialized, and fine-tuning modifies them for the new dataset without losing generic in-formation from pre-training. In time-sensitive applications like depression pattern identification with limited training data, fine-tuning is crucial. It optimizes pre-trained models, saving time and effort by building on past information. Deep learning and model training for specific tasks are optimized using this method, even with a smaller dataset. Fine-tuning adapts the pre-trained model's general knowledge to the new classification task, yielding results like training from the start with less data. Fine-tuning hyperparameters for MobileNetV2 involves optimizing the model's performance by selecting the best combination of hyperparameters based on the specific dataset and task at hand, as visually displayed in Fig. 6.

MobileNetV2 comprises two types of blocks: residual blocks with a stride of 1 and non-residual blocks with a stride of 2, primarily used for downsizing. The model consists of 155 layers, including the classification layer. Our approach utilizes this model to extract features from 2D depression images. In our proposed model, we leverage 154 pre-trained network layers from the convolutional base, with the addition of two extra layers—one at the start for preprocessing and one at the end for task-specific classification—using the Adaboost classifier.

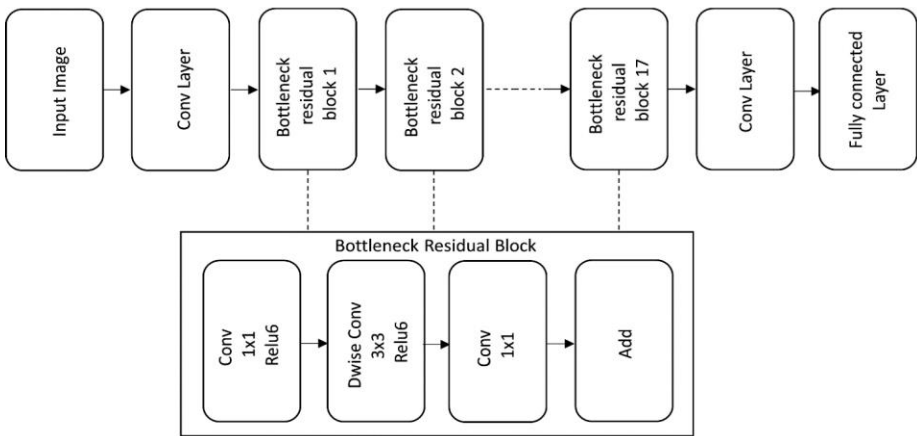


Fig. 5. A MobileNet-based CNN model with a novel fine-tuning mechanism for depression patterns detection.

The classification process, illustrated in Fig. 6, involves passing inputs through the layers obtained during the fine-tuning process. Initially, we train the entire model for 50 epochs before fine-tuning. In the first fine-tuning step, we unfreeze the last 50 layers of the convolutional base and create new training loops, totaling 80 epochs (as indicated by green bars in Fig. 7). For the second fine-tuning phase, we progressively unfreeze layers from the end of the convolutional base using a step function. We reduce the number of unfrozen layers by five for every eight cycles, shown in green bars in Fig. 7. In our last approach, instead of following a predefined order, we determined the number of epochs and which layers to unfreeze based on a predefined exponential equation (Eq. (2)). This equation allows us to adaptively decrease the number of training cycles from the last layer to a specified depth during training.

$$\sigma(x) = \frac{1}{1+e^{-x}} \tag{2}$$

Using this approach, we can preserve more pre-trained generic information. CNN models' later layers often possess specialized learned properties, while the initial layers focus on generic properties like edges, shapes, and textures. We use a learning rate of 0.0001 and the Adam optimizer for training. The fine-tune stage minimizes model size and speeds up detection; however, MobileNetV2's conventional layer is limited. The model's accuracy matches CNN's. Thus, MobileNetV2 network optimization is essential. This study replaces standard convolutions with "depth-wise separable convolution" to improve the MobileNetV2 architecture. Depth-wise separable convolution reduces training weight factors and floating-point workloads, making the model lighter, quicker, and more accurate. Standard convolution extracts characteristics using different convolution kernels by simultaneously controlling the input channel and convolution window. In depth-wise separable convolution, two jobs are carried out separately. To ensure equal input and output channels, the initial convolution in space is performed individually on each input channel using a single 1-dimensional kernel. To project the calculated channels onto a new channel space, point-based convolution with a 1 × 1 kernel (PointwiseConv) is used, as shown in Fig. 7. The classical convolution is represented by Eq. (3). While the depth-wise separable convolution is mathematically represented by Eq. (3)–(6):

$$Basic-Conv(\theta,x)_{(i,j)} = \sum_{h,w,c}^{H,W,C} \theta(h,w,c).x(i+h,j+w,c) \tag{3}$$

$$DepthwiseConv(\theta,x)_{(i,j)} = \sum_{h,w}^{H,W} \theta(h,w) * x(i+h,j+w) \tag{4}$$

$$PointwiseConv(\theta,x)_{(i,j)} = \sum_{c}^{C} \theta_c \times (i,j,c) \qquad (5)$$

$$SeparableConv(\theta_p,\theta_d,x)_{(i,j)} = PointwiseConv_{(i,j)}(\theta_p, DepthwiseConv_{(i,j)}(\theta_d,x)) \qquad (6)$$

Fine-tuning hyperparameters often involves conducting a grid search or random search over the hyperparameter space and evaluating the model's performance on a validation set.

The hyperparameter values that result in the best performance are then selected for the final model as described in Algorithm 2, ensuring MobileNetV2 is well-suited for the early detection of depression patterns using EEG and HRV signals. To detect depression patterns early, utilizing EEG and HRV data, MobileNetV2's parameters and design must be fine-tuned. Customizing pre-trained models for broad computer vision applications on big datasets is common. Fine-tuning MobileNetV2 involves these steps:

Algorithm 2: Fine-tunning MobileNet architecture for features extraction

Input: M: Pre-trained MobileNetV2 model with weights

[Initialize Parameters]
Fine-tuning dataset: D
Number of classes: C
Learning rate: LR
Number of epochs: epochs
Batch size: batch-size
Dropout rate: dropout-rate

Output: $M\_fine-tuned$: fine-tuned MobileNetV2 model

M = Pre − trained (MobileNetV2, W);
F = Freeze (M, $initial-layers$ = 100);
U = Update − classification − layer (M, $AdaBoost-classifier$, C);
O = optimizer = Adam (M, learning_rate = LR);
For each **validation-*accuracy* is not satisfied do**
D = Dropout (M, dropout − rate);
C = Compile(optimizer = optimizer, loss = $\sigma(x)$, metrics = ['accuracy']);
E = Model. fit(D, epochs = epochs, batch_size = batch_size, validation_split = 0.2);
R = LR × 0.1; Reduce the learning rate
dropout − rate = dropout − rate × 0.9; Reduce the dropout for regularization
epochs = epochs + 5; Increase epochs for further training
[End for Loop]
Function Improve-Fine-tune (M):
F = UnFreeze (M, $layers$ = 100);
U = Update − classification − layer (M, $AdaBoost-classifier$, C);
O = optimizer = Adam (M, learning_rate = LR);
For each **validation-*accuracy* is not satisfied do**
C = Compile(optimizer = optimizer, loss = $\sigma(x)$, metrics = ['accuracy']);
E = Model. fit(D, epochs = epochs, batch_size = batch_size, validation_split = 0.2);
epochs = epochs + 5; Increase epochs for further training
[End for Loop]
Return ($M\_fine-tuned$);
End of algorithm

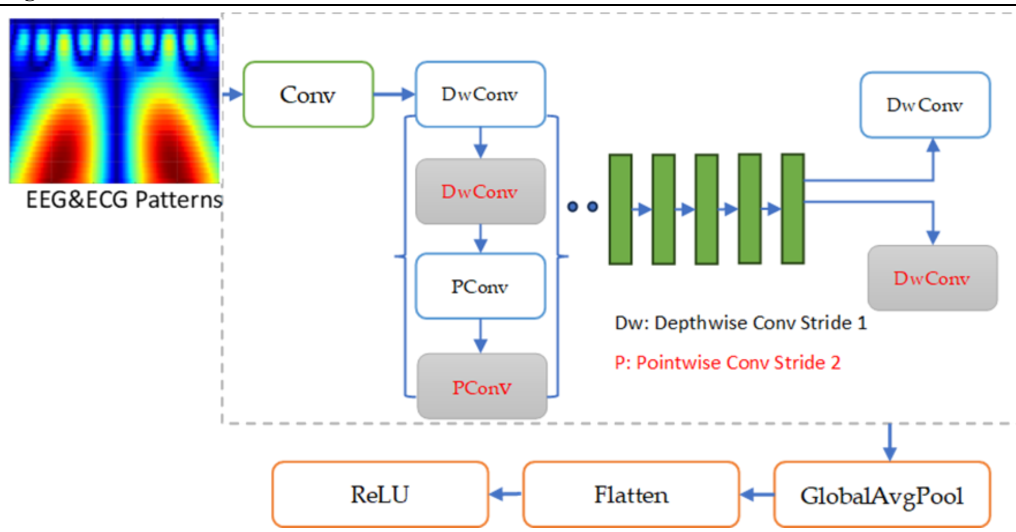


Fig. 6. A MobileNet-based CNN model with a novel fine-tuning mechanism for depression pattern detection.

Load ImageNet weights into the pre-trained MobileNetV2 model. These pre-trained weights provide a foundation for fine-tuning visual elements. Freeze Mo-bileNetV2's earliest layers to avoid overfitting and preserve low-level feature knowledge. These layers record basic patterns and textures that are transportable be-tween activities. Change MobileNetV2's classification layer to identify depressive patterns. This new layer may have fully linked (dense) layers, dropout layers for regularization, and an output layer with enough classes (depressed and non-depressed), depending on the job. Set a slower, fine-tuning learning rate. Fewer learning rates allow the model to make fewer alterations to pre-trained weights, eliminating abrupt changes that might damage learned features.

We train the improved MobileNetV2 model using EEG- and ECG-based HRV measurements with depression labels. Batch normalization and data augmentation promote generalization and prevent overfitting. Based on validation findings, alter hyperparameters such as learning rate, dropout rate, and the number of neurons in the new classification layer. Unfreeze more layers. If the fine-tuned model performs poorly on the validation set, unfreeze more MobileNetV2 layers to let it adjust its learned features to the job. Fine-tune the model until the validation set achieves the required accuracy and generalization. Assess the fine-tuned model: Finally, test the fine-tuned Mo-bileNetV2 model on a second test set to detect depression patterns from EEG and HRV signals. To assess the model's performance, provide accuracy, sensitivity, specificity, and AUC. Following these processes, the fine-tuned MobileNetV2 network uses its pre-trained information and adapts to fresh data to detect depression tendencies early, utilizing EEG and ECG signals.

E. Patterns Recognition

In our second experimental approach, we replaced the softmax classifier, which serves as the top layer of the MobileNet V2 model, with a dropout AdaBoost classifier. We made this substitution to explore an alternative to the traditional deep CNN with a softmax top layer. Our objective was twofold: first, to potentially enhance performance, and second, to mitigate the risk of overfitting during classification testing.

The complete MobileNet V2 architecture comprises 17 consecutive bottleneck residual blocks, followed by a standard 1×1 convolution layer, a global average pooling layer, and a softmax classification layer. Consequently, a set of valuable features was extracted from 2D scalogram patterns using the output of the global average pooling layer within the MobileNet V2 base model. Once this feature extraction process was finalized, the extracted features were inputted into an AdaBoost classifier.

AdaBoost is a linear model employed to address data classification challenges. AdaBoost excels at solving both linear and non-linear classification problems. In essence, AdaBoost's primary role is to determine or compute a separating line that effectively distinguishes multiple classes for any given case. It operates by taking input data and producing an optimal line that effectively separates these classes. This optimal line signifies a generalized separator that accommodates all classes as a well-rounded classification boundary. The Adaboost must handle multi-class classification in our study. In other words, we required AdaBoost to classify five depression patterns, each containing 500 distinct depression classes. AdaBoost resolves multi-class classification problems by transforming the single multi-class problem into numerous binary classification problems, processing them using a standard AdaBoost linear classification approach via the one-versus-all methodology. The one-versus-all approach involves building binary classifiers that distinguish between one specific label and all other labels. It is important to note that AdaBoost predictions yield outcomes similar to those obtained using the softmax function. However, the distinction lies in AdaBoost's emphasis on finding the maximum margin between data points from different classes, whereas the softmax function minimizes cross-entropy or maximizes log-likelihood.

Our approach uses an ensemble learning approach based on a fine-tuned MobileNet architecture with an AdaBoost classifier to accurately predict depression patterns like major depressive state (MDS), cognitive and emotional arousal (CEA), mood disorder patterns (MDP), mood and emotional regulation (MER), and stress and emotional dysregulation (SED). These depression patterns have been gathered from two publicly available datasets, MODMA and SWEEL-KW. Real-time signal processing on wearable IoT devices requires computational efficiency, which MobileNetV2 provides due to its lightweight architecture. Therefore, this model balances processing speed and prediction accuracy with depth-wise separable convolutions. AdaBoost, an ensemble learning technique, improves the model's predictive accuracy by combining numerous weak learners to produce a strong predictive model, minimizing bias and variation to assure prediction dependability. This methodological fusion outperformed other depressive pattern prediction methods.

It is also important to discuss how the amount of the extracted pattern affects model performance. Our ensemble learning-enhanced model may steadily improve its prediction ability by absorbing more patterns. While a limited number of patterns may initially limit performance, the model's design enhances its predictive abilities with increased data exposure, thereby improving its ability to identify depressive states.

IV. Experimental Results

Several important parts make up the experimental setup for finding early signs of depression using machine learning and deep learning with scalogram-like patterns. This section outlines the experimental design, model training, evaluation, and performance metrics used in the study. To detect depression patterns early, utilizing machine learning and deep learning using EEG and ECG-based HRV inputs in the form of a 2D scalogram, software libraries, frameworks, and hardware must be configured. Here are the main environment setup tasks: Create a Python environment, ideally virtual, to separate project dependencies. Install Python 3.6.15. Download TensorFlow or PyTorch, a deep learning framework for neural network training. These frameworks provide MobileNetV2 pre-trained models and fine-tuning tools. Jupyter Notebook provides interactive and repeatable research. You can combine code, graphics, and markdown in one document. CPU, RAM, and storage must fulfill the computational needs of training deep learning models on the given dataset. Consider GPUs for quicker training if available.

Table III lists the study's MobileNetV2 and AdaBoost hyperparameters for depression detection. MobileNetV2 settings include learning rate (0.001), batch size (128), epochs (40), dropout rate (0.3 or 0.5), optimizer (Adam), convolutional layer filters (128), alpha (width multiplier, 0.75), and input picture size (224 × 224). The base estimator (logistic regression), number of estimators (200), learning rate (0.1), loss function (exponential), and maximum depth of weak learners (5) are AdaBoost settings. The model's learning and depression pattern recognition depend on these hyperparameters.

Image classification requires loss function and accuracy during transfer learning (TL) training. Optimizers optimize network weights and learning. This step minimizes DL layer training loss functions. In this work, ADAM, SGD, Adadelta, AdaBelief, and RMSprop optimizers changed each pre-trained TL model layer's weight and acceleration time. The optimizer in DL algorithms controls weight and bias during network fitting. The optimizer prioritizes this. We choose the best layer feature map, filter size, activation function, pool size, dropout, and fine-tuning hyperparameters. To get the best settings, optimization was done. The role of each optimizer in deep learning is explained. In contrast, AdaBelief optimization chooses deep learning framework assessment hyperparameters. This research employs 12 hyperparameters. Studying hyperparameters and fine-tuning layers, including freezing the top or bottom network layer. To find the best layers and hyperparameters, automated and fine-tuning approaches are being tested. When assessing the hyperparameter and fine-tuning pre-trained layers, AdaBelief sets a default value. The second stage analyzes transfer learning (TL) models after automatic hyperparameter tweaking and fine-tuning against all TL models using different optimizations. The third section evaluates TL with frozen layers during automated hyperparameter adjustment. Every TL model has hyperparameters and fine-tuning.

Table IV compares the average processing time for transfer learning (TL) algorithm stages and the suggested architecture on the MODMA and SWELL-KW datasets. We tested VGG16, AlexNet, Xception, MobileNet, Inception, and MobileNet-Finetune. We present preprocessing, feature extraction, training, prediction, and processing time for each approach. This stage prepares the data for analysis. AlexNet (20.4 s), Xception (19.2 s), MobileNet (15.3 s), Inception (12.7 s), and MobileNet-Finetune (2.8 s) preprocess faster than VGG16 (24.9 s). Data feature extraction selects relevant characteristics. VGG16 has the longest feature extraction time at 17.4 s, followed by AlexNet (15.5 s), Xception (16.2 s), MobileNet (14.2 s), Inception (12.5 s), and MobileNet-Finetune (2.3 s), the last being the fastest.

This stage trains the model with the extracted characteristics. At 220.5 s, VGG16 takes the longest to train, followed by AlexNet (230.5 s), Xception (235.5 s), MobileNet (230.5 s), Inception (268.5 s), and MobileNet-Finetune (120.5 s). Prediction relies on the training model. VGG16 takes 12.8 s to forecast, followed by AlexNet (10.8 s), Xception (7.8 s), MobileNet (9.8 s), Inception (8.8 s), and MobileNet-Finetune

TABLE III. HYPERPARAMETERS USED IN THIS STUDY ARE OUTLINING MOBILENETV2 AND ADABOOST FOR IDENTIFICATION OF DEPRESSION PATTERNS

Model	Hyperparameter	Description	Possible Values
MobileNetV2	Learning rate	Step size for updating model parameters	0.001
	Batch size	Number of samples used in each training batch	128
	Number of epochs	Number of times the model iterates over dataset	40
	Dropout rate	Fraction of neurons to randomly drop during training	0.3, 0.5
	Optimizer	Algorithm for optimizing model weights	Adam
	Number of filters	Number of filters in convolutional layers	128
	Alpha	Width multiplier to reduce model size	0.75
	Input image size	Dimensions of the input image	224 × 224
AdaBoost	Base estimator	The weak learning model used in boosting	Logistic Regression
	Number of estimators	Number of weak learners in the ensemble	200
	Learning rate	Weight of each weak learner in the ensemble	0.1
	Loss function	The loss function used for boosting	Exponential
	Maximum depth	Maximum depth of the weak learners (trees)	5

TABLE IV. AVERAGE PROCESSING TIME ON TRANSFER LEARNING (TL) ALGORITHMS COMPARED TO PROPOSED ARCHITECTURE BASED ON ALL SELECTED PATTERNS (MAJOR DEPRESSIVE STATE (MDS), COGNITIVE AND EMOTIONAL AROUSAL (CEA), MOOD DISORDER PATTERNS (MDPS), MOOD AND EMOTIONAL REGULATION (MER), AND STRESS AND EMOTIONAL DYSREGULATION (SED)) FROM MODMA AND SWEEL-KW DATASETS

Method	Preprocessing	Feature Extraction	Training	Prediction	Overall
VGG16	24.9 s	17.4 s	220.5 s	12.8 s	275.6 s
AlexNet	20.4 s	15.5 s	230.5 s	10.8 s	277.2 s
Xception	19.2 s	16.2 s	235.5 s	7.8 s	278.7 s
MobileNet	15.3 s	14.2 s	230.5 s	9.8 s	269.8 s
Inception	12.7 s	12.5 s	268.5 s	8.8 s	302.5 s
MobileNet-Finetune	2.8 s	2.3 s	120.5 s	2.6 s	128.2 s

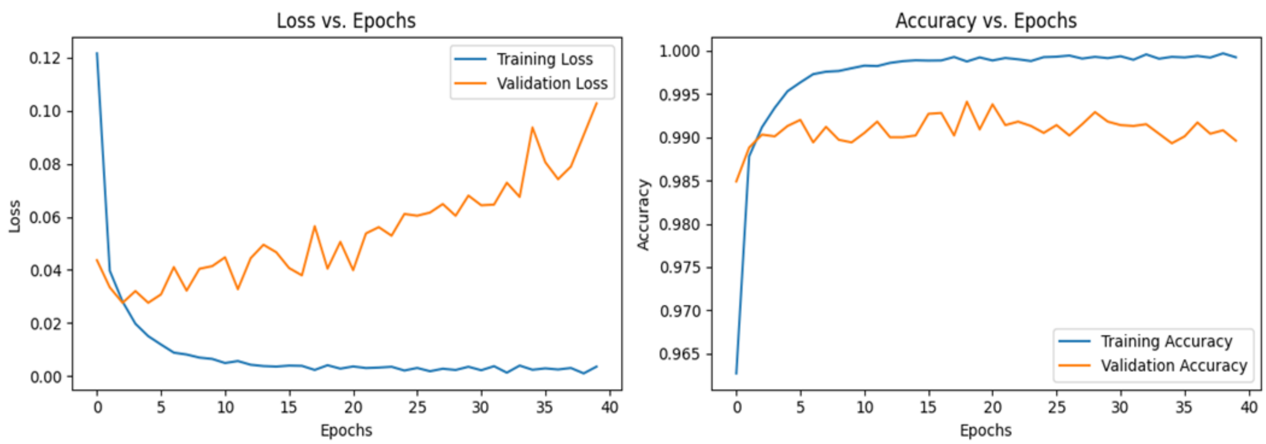
TABLE V. THIS TABLE REPRESENTS THE COMPUTATIONAL COMPLEXITY BASED ON TYPICAL ASPECTS LIKE THE NUMBER OF PARAMETERS, FLOATING-POINT OPERATIONS PER SECOND (FLOPS), AND MEMORY REQUIREMENTS

Model	Number of Parameters	FLOPs	Memory Requirement
VGG16	138 million	15.5 billion	High
AlexNet	60 million	1.5 billion	Moderate
Xception	22 million	8.4 billion	Moderate
MobileNet	4.2 million	569 million	Low
Inception	23 million	5.7 billion	Moderate
MobileNet-Finetune	3.2 million	1.3 billion	Low

(2.6 s), the fastest. All stage processing times are in this column. The longest processing time is 275.6 s for VGG16, followed by AlexNet (277.2 s), Xception (278.7 s), MobileNet (269.8 s), Inception (302.5 s), and MobileNet-Finetune (128.2 s), the shortest. This table shows that MobileNet-Finetune is the most efficient solution for the investigated datasets due to its faster processing time across all stages.

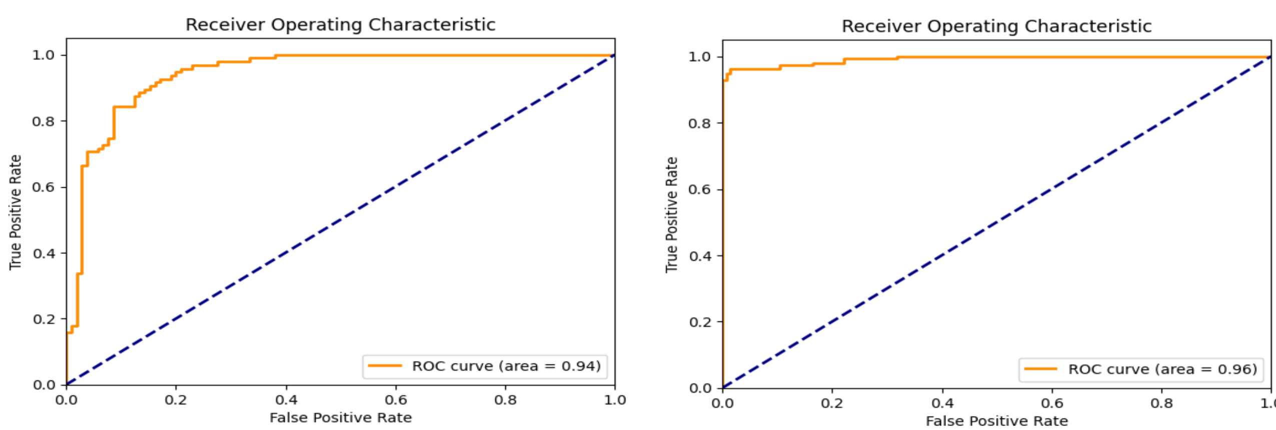
It is vital to note that computational complexity depends on model architecture, implementation, and evaluation hardware. Based on the above hardware characteristics, we are calculating explicit computational processes.

Table V shows that earlier, more parameterized models like VGG16 and AlexNet had higher computational complexity and memory needs. Modern models like MobileNet are efficient, reducing computational and memory needs. The proposed "MobileNet-Finetune" denotes a custom-tuned version of MobileNet with computational complexity and memory demand tailored to specific workloads to maintain efficiency and optimize performance. FLOPs and memory needs are described in this table.



(a) (b)

Fig. 7. Loss versus accuracy curves for training and validation with respect to epochs for pro-posed depressive-deep system, where figure (a) shows the training and validation loss curves, (b) represents the training and validation accuracy curves.



(a) (b)

Fig. 8. Area under the curve (AUC) for depression patterns identification based on collected scalogram, where depressive-deep AUC (a) without fine-tune curve, and (b) with fine-tune net-work.

By following these steps, the proposed system is ready for the early detection of depression patterns using ML and DL with an ensemble of scalogram-like EEG- and ECG-based patterns. This setup allows researchers to experiment with different models and hyperparameters systematically, ensuring reproducibility and facilitating further research in the field of mental health diagnostics. We evaluated the proposed system using these criteria and compared it to pre-trained transfer learning techniques. We also utilized AUC to demonstrate the training and validation dataset's efficacy with a 10-fold cross-validation test. Fig. 7 shows the proposed SqueezeNet-Light model's best plot loss, accuracy, AUC, and recall on the train and validation sets with data augmentation across 40 epochs.

Fig. 8 illustrates the loss and accuracy trends concerning the epochs during the training and validation phases of the proposed depressive-deep system. The loss curve shows model parameter optimization as the loss function decreases after training. The model's prediction performance on both the training and validation datasets improves as the accuracy curve rises across epochs. These graphs reveal Deep's training dynamics and generalization capabilities in recognizing depressed patterns. This study trains its deep learning model via backpropagation. The right optimizer is chosen to guarantee this deep learning model converges. The deep learning literature uses optimizers like SGD, RMSprop, and adaptive moment estimation (Adam). Because adaptive optimizers are beneficial, the Adam optimizer with an initial learning rate of 10^{-4} was used for this investigation. Due to computer memory limits, the batch size was twenty, with 29 steps. Model training lasted 40 epochs.

Fig. 9 illustrates the confusion matrix depicting the results obtained by the proposed depressive-deep model in comparison to normal human assessments for the identification of various depression patterns, including major depressive state (MDS), cognitive and emotional arousal (CEA), mood disorder patterns (MDPs), mood and emotional regulation (MER), and stress and emotional dysregulation (SED). This matrix shows how the model performs across different depression patterns, allowing comparisons with human assessments and revealing areas of agreement and disagreement. In this figure, our study includes a 'normal' class with depression patterns to evaluate the depressive-deep model's diagnostic skills. This categorization helps the model discriminate between depressed states and non-depressive states. This class dataset, with the same size as other depression patterns, was collected from publicly available datasets (MODMA and SWEEL-KW). By comparing the model's predictions to human evaluations, we want to show that it may help mental health practitioners identify people without depression for early intervention and individualized therapy.

The confusion matrix in Fig. 10 shows the results of the suggested depressive-deep model for identifying MDS, CEA, MDP, MER, and SED depression patterns compared to non-depressive or normal patterns. This matrix provides a detailed analysis of the model's predicted accuracy and opportunities for improvement across depression categories.

Table VI presents the performance evaluation of the proposed depressive-deep model for the identification of five distinct depression patterns. Each row represents a different combination of feature extraction (f) and classification (c) methods. The metrics assessed include accuracy (ACC), sensitivity (SE), specificity (SP), precision (P), F1-score, and Matthew's correlation coefficient (MCC). The results indicate that the depressive-deep model, utilizing fine-tuned MobileNet V2 for feature extraction and AdaBoost for classification, achieved the highest performance across all metrics, with an accuracy of 0.96, sensitivity of 0.98, specificity of 0.95, precision of 0.95, F1-score of 0.96, and MCC of 0.96. Currently employed clinical diagnostic tests exhibit significant limitations, particularly in terms of the false negative rate. The false positive and false negative rates of a model can be visualized using specificity and sensitivity scores.

Table VII for depression pattern identification reveal notable trends. The SOTA comparisons were performed on various current studies, which we had implemented and tested on selected depression patterns. While traditional machine learning approaches like those in [22] achieve respectable accuracies (90.00%) with nonlinear features and logistic regression on EEG data, they may lack generalizability. Deep learning models such as the CNN + LSTM model in [23] achieve impressively high accuracies (99.07% right, 98.84% left) on EEG signals but are complex and computationally intensive. Similarly, ensemble learning coupled with deep learning, as seen in [24], achieves competitive accuracies (89.02%) but may be sensitive to feature selection. Methods focusing on specific EEG features like functional connectivity in [25] or specific patterns in [27] yield high accuracy (up to 96.00%) but may be limited in scope. Meanwhile, more advanced deep learning architectures like the DWSN model in [28] achieve near-perfect accuracy (up to 99.95%) but may require substantial computational resources. In contrast, the proposed depressive-deep architecture achieves competitive accuracy (up to 96.00%) while potentially addressing issues of computational complexity and feature scope present in some state-of-the-art methodologies.

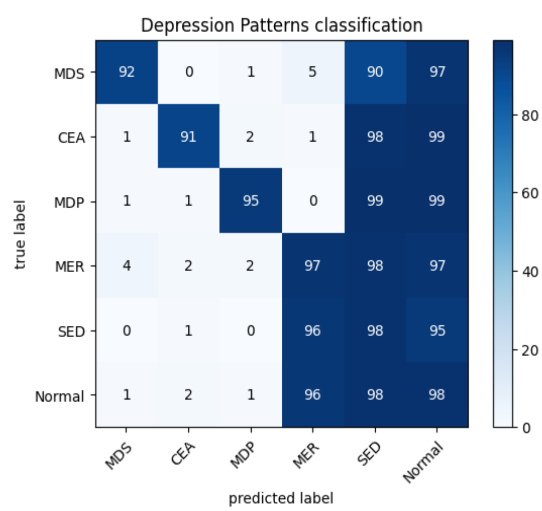


Fig. 9. Confusion matrix for results obtained by a proposed depressive-deep model with various identification of depression patterns such as major depressive state (MDS), cognitive and emotional arousal (CEA), mood disorder patterns (MDPs), mood and emotional regulation (MER) and stress and emotional dysregulation (SED) patterns.

However, when we applied these state-of-the-art systems to five different depression patterns and utilized our dataset, they achieved very low accuracy, as described in Table VII. For comparison, we have selected a diverse set of studies representing different methodologies for depression pattern identification. These include traditional machine learning approaches such as machine learning with nonlinear features and logistic regression [22], as well as more advanced deep learning architectures like deep learning with CNN and LSTM [23] and deep learning with DWSN [28]. Studies focusing on specific EEG features like functional connectivity [25] and specific hemispheres [27] also include ensemble learning methods. Additionally, the comparison encompasses various combinations of machine learning algorithms such as SVM, LR, and NB [25], as well as hybrid models like CNN-LSTM [26]. This selection provides a comprehensive overview of the methodologies employed in the field of depression pattern identification, allowing for a thorough evaluation of the proposed depressive-deep architecture against state-of-the-art approaches. The table compares different models used for identifying depression patterns based on their performance metrics. Each model is assessed for its accuracy, sensitivity, average processing time, and number of parameters. Among the models, the proposed depressive-deep architecture, employing MobileNet V2, stands out with a high accuracy score of 0.96 and sensitivity of 0.98. Importantly, it achieves

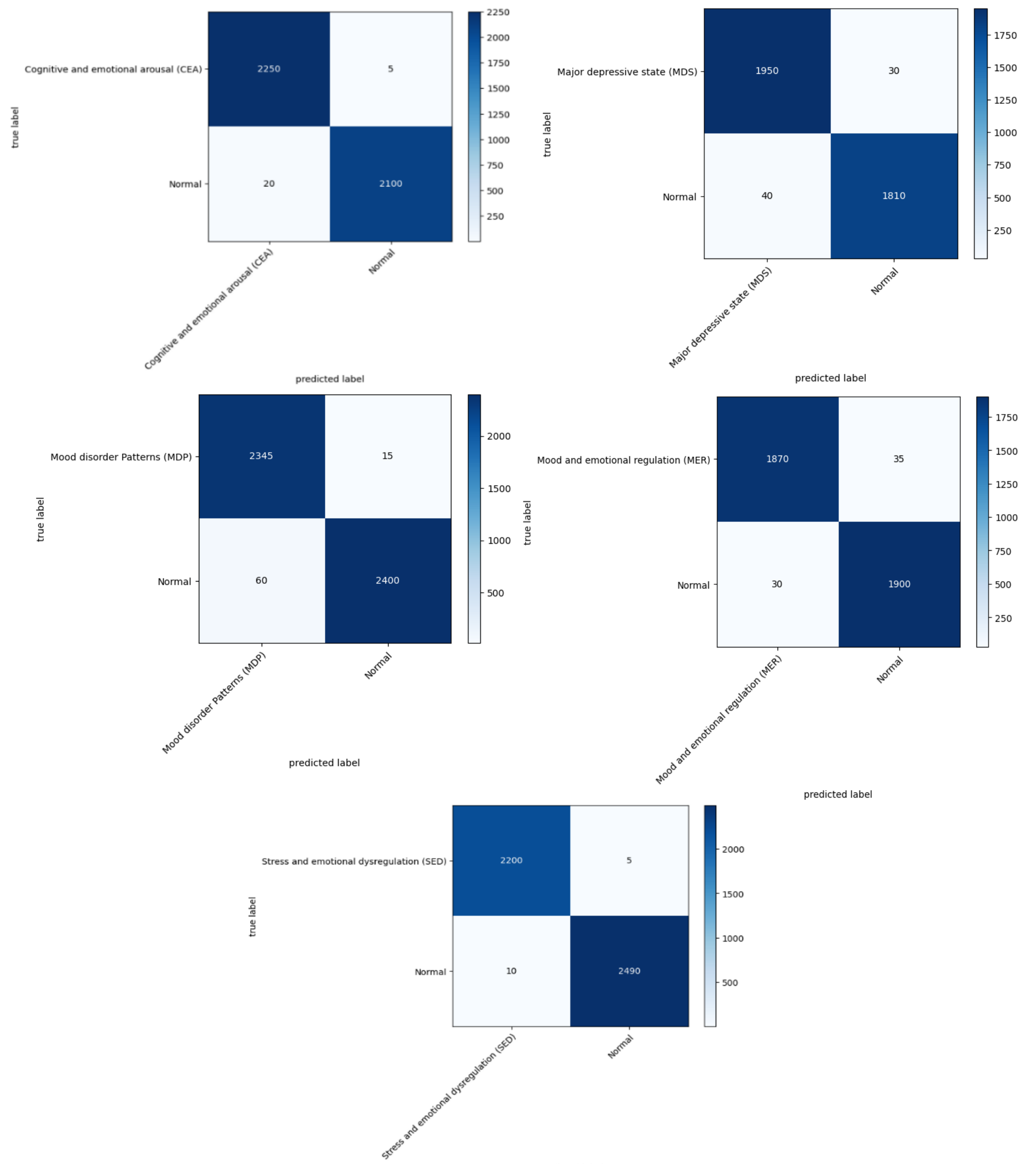


Fig. 10. Confusion matrix for results obtained by a proposed Depressive-Deep model with various identification of depression patterns compared to normal human. Those patterns are major depressive state (MDS), cognitive and emotional arousal (CEA), mood disorder patterns (MDP), mood and emotional regulation (MER) and stress and emotional dysregulation (SED).

these impressive results while requiring substantially fewer parameters (12.54 million) compared to other models. This suggests that the proposed architecture offers a promising approach for accurately detecting depression patterns with efficiency. The NeuroSky Mind Wave headset serves as the primary brain–computer interaction (BCI) device [38,39] utilized in this study, offering a single-channel interface for EEG signal acquisition. Coupled with a Raspberry Pi board, an example of an IoT device, the MindWave headset enables the capture of EEG signals, while ECG signals are obtained using the MikroElektronika Heart Rate Variability (HRV) ECG sensor. To check model generalizability, we have included five patient signals. These devices are lightweight and non-invasive, making them suitable for continuous monitoring throughout the day. Our first findings indicate that shorter, carefully planned sessions might provide substantial predictive utility, while longer monitoring periods may improve model performance by recording a wider variety of physiological responses. We observed that several-hour sessions can produce enough data to uncover depressive trends in this investigation. This period balances comprehensive data with gadget wear in daily living.

TABLE VI. PERFORMANCE OF PROPOSED DEPRESSIVE-DEEP FOR IDENTIFICATION OF FIVE HEART AND BRAIN PATTERNS BASED ON ENSEMBLE-BASED SCALOGRAM IMAGES

Model (Features Extraction (f) + Classification(c)	* ACC	* SE	* SP	* P	* F1-Score	* MCC
f = MobileNet V2, c = Softmax	0.90	0.87	0.88	0.87	0.88	0.90
f = CNN, c = MobileNet2	0.91	0.89	0.88	0.90	0.89	0.90
f = MobileNet V2, c = AdaBoost	0.92	0.88	0.89	0.90	0.91	0.91
Depressive-Deep: f = Fine-tune MobileNet 2,c = AdaBoost	0.96	0.98	0.95	0.95	0.96	0.96

TABLE VII. STATE-OF-THE-ART COMPARISONS FOR IDENTIFICATION OF BRAIN AND HEART PATTERNS

Study	Model	* ACC	* SE	Average Time (s)	Parameters
[22]	Logic Regression	0.74	0.76	5.242	--
[23]	CNN + LSTM	0.86	0.80	3	20.24 M
[24]	Ensemble DL	0.97	0.91	2.5	248.35 M
[25]	SVM-LR-NB	0.86	0.96	6.5	--
[26]	CNN-LSTM	0.88	0.88	3.136	24.56 M
[27]	CNN	0.91	0.91	4.5	267.20 M
[28]	DWSN	0.90	0.90	4	343.67 M
Proposed	MobileNet V2	0.96	0.98	0.043	12.54 M

* SE: sensitivity, ACC: accuracy.

These signals are then processed to extract patterns indicative of depression. For the classification of depression patterns, a fine-tuned and lightweight MobileNetV2 model, integrated with an Adaboost network, was employed. The model was trained and evaluated using TensorFlow on the Colab Google platform. To enable deployment on IoT devices [40], like Raspberry Pi boards, the TensorFlow model was further optimized into a TensorFlow Lite model.

The described study focuses on the use of IoMT-based wearable devices for identifying depression patterns through a proposed model called depressive-deep. This model is designed to detect various types of depression patterns, including major depressive state (MDS), cognitive and emotional arousal (CEA), mood disorder patterns (MDPs), mood and emotional regulation (MER), and stress and emotional dysregulation (SED). The results obtained from the depressive-deep model are visualized in two figures. Fig. 11 illustrates the distribution of each category of depression patterns, providing insights into the prevalence or occurrence of different types of depression. This result helps researchers and practitioners understand the depressive-deep model's performance and effectiveness in identifying depression patterns using IoMT-based wearable devices. On average, 96% accuracy is achieved by the proposed system.

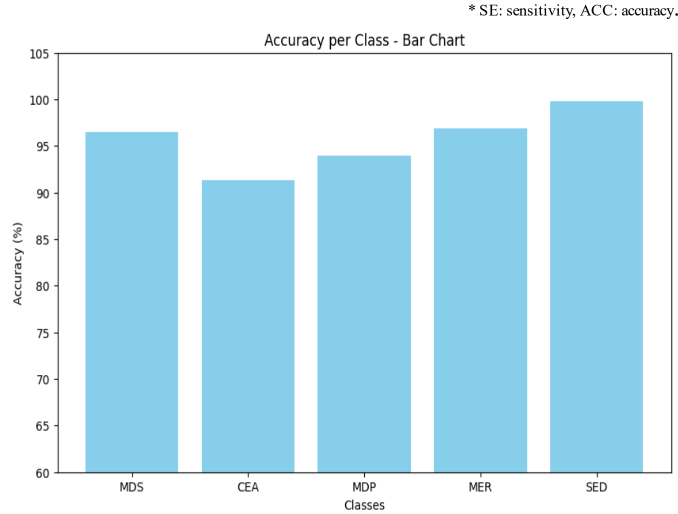


Fig. 11. IoMT-based wearable identification depression patterns results obtained by proposed depressive-deep model with various identification of depression patterns such as major depressive state (MDS), cognitive and emotional arousal (CEA), mood disorder patterns (MDPs), mood and emotional regulation (MER) and stress and emotional dysregulation (SED). Figure (a) shows the distribution of each category of brain and heart depression patterns.

V. Discussions

This work used an ensemble of EEG and HRV data in 2-D scalogram pictures to detect depressive patterns using machine learning and deep learning. These new computational tools can help diagnose and treat depression early, improving mental health outcomes.

MobileNetV2 and AdaBoost ensemble learning showed promising depression prediction results. The lightweight MobileNetV2 architecture handled HRV and EEG data and performed well. Using AdaBoost in ensemble learning made the model more accurate, sensitive, specific, precise, and higher in F1-score and AUC, making it a strong depression classifier. The 96% accuracy shows that these methods may early detect depression and provide therapy. Fig. 4 shows the suggested Depressive-Deep model's scalogram. This scalogram shows major depressive state (MDS), cognitive and emotional arousal (CEA), mood disorder patterns (MDP), mood and emotional regulation (MER), and stress and emotional dysregulation. The scalogram shows these different depression patterns holistically by integrating EEG and HRV data, revealing the intricate relationships and dynamics of depressed states.

The data analysis section describes how machine learning and deep learning using an ensemble of scalogram-like EEG and HRV patterns may detect depressive patterns early. This method allows researchers to systematically test different models and hyperparameters, ensuring repeatability and advancing mental health diagnosis. Fig. 5 shows the loss and accuracy trends during training and validation of the proposed Depressive-Deep system, demonstrating model parameter optimization and prediction performance improvement. The discussion also covers deep learning model training, stress optimizer selection, and model convergence. In Fig. 8, the AUC values for recognizing depression patterns from scalograms show the Depressive-Deep system's discriminatory capability before and after network fine-tuning. Confusion matrices in Fig. 9 an Fig. 10 show how well the model identifies depressive patterns, allowing comparisons with human judgments. Table V further compares the suggested Depressive-Deep model's accuracy and sensitivity across feature extraction and classification approaches, showing its superiority. Comparing the proposed Depressive-Deep architecture to state-of-the-art depression pattern identification methods shows that it achieves competitive accuracy while addressing computational complexity and feature scope issues. Finally, Table VII compares model performance characteristics, showing that the Depressive-Deep architecture is more accurate and efficient. These findings demonstrate the depressive-deep system's ability to detect depressive patterns early, advancing mental health diagnoses.

Despite the encouraging results, this study admits some limitations that should be addressed when interpreting the data. Small datasets may limit the model's generalizability; therefore, validation on bigger, more diverse datasets is necessary. Deep learning models like MobileNetV2 are difficult to comprehend, requiring greater study into ways to explain their judgments.

Future studies can use neuroimaging and self-report questionnaires to better understand depression trends. Additional deep learning architectures and transfer learning methods may increase model performance and interpretability. Actual specialists and mental health professionals will help translate the suggested model into actual practice to improve depression identification and treatment. The new study re-fines the machine learning and deep learning models for early depression identification, utilizing EEG and HRV data. The research team is optimizing hyperparameters, im-proving feature selection, and testing the interpretation of model predictions. We are also validating the model on larger and more diverse datasets to ensure its resilience and generalizability across populations. To assess the model's clinical applicability, mental health specialists and clinical experts are working together. The study team is using domain expert comments to make the model more practical and adaptable to clinical situations. This iterative approach guarantees that the model meets clinical demands and integrates seamlessly into the healthcare system.

Future studies will go beyond EEG and HRV depression identification. The team wants to use neuroimaging, self-reported questionnaires, and wearable sensor data to measure mental health holistically. The model can capture more physiological and behavioral indicators related to mental health issues by using several data modalities, resulting in a more accurate and tailored diagnosis. To increase model performance and interpretability, transfer learning and deep learning architectures are another possibility. We can fine-tune pre-trained models for depression identification using EEG and HRV data, potentially enhancing efficiency and accuracy.

Implementation of the suggested concept into user-friendly applications or tools for mental health professionals and individuals is underway. The objective is to create an accurate and easy-to-use tool for early depression identification and continuous monitoring to enhance mental health outcomes and reduce the burden of global mental health problems. The study team also plans to undertake longitudinal studies to test the model's ability to forecast depression onset and track treatment success. Understanding the model's predictive powers beyond diagnosis will help identify depression risk fac-tors and enable focused therapy.

Current and future work aims to transform mental health diagnosis using machine learning and deep learning. The research aims to produce a tool that aids early diagnosis and provides mental health providers with significant information for tailored treatment planning by refining and expanding the model. The ultimate objective is to enhance mental health diagnosis, management, and treatment worldwide to improve well-being and results. The model was accurate, although the study acknowledged a tiny dataset. The model needs additional validation on larger and more diverse datasets to be more generalizable. Exploring various deep learning architectures and transfer learning methods may increase model performance and interpretability. Smartphones are essential for people. Mobile Crowd Sensors (MCS) uses mobile device sensors and computing [12]. MCS lets users exchange data and get insights to measure and track shared activities. This strategy is essential for the development of IoT applications. MCS will be used to identify depression-like characteristics in the future. Moreover, a future study will compare multi-day and single-day observations to determine the minimal time for reliable forecasts. We want to find the best balance between model accuracy and user convenience. We appreciate your ideas and believe that studying measurement length and prediction accuracy is essential for BCI and IoT-based mental health monitoring system implementation.

Our research compares accuracy, sensitivity, specificity, precision, F1-score, MCC, and AUC of the proposed depressive-deep model to state-of-the-art depression detection techniques to demonstrate its benefits. Our model outperforms existing approaches with a 96% accuracy rate using the lightweight and efficient MobileNetV2 architecture and the AdaBoost ensemble learning algorithm. EEG and HRV data integrated into 2D scalograms provide a holistic view of depressive patterns, allowing the model to capture intricate relationships and dynamics in the data, making early depression detection more comprehensive and effective.

The findings suggest that machine learning and deep learning can detect depression patterns in EEG and HRV data early. A visual diagram of a scalogram generated by a proposed Depressive-Deep model to embed all depression patterns such as major depressive state (MDS), cognitive and emotional arousal (CEA), mood disorder patterns (MDP), mood and emotional regulation (MER), and stress and emotional dysregulation (SED) into one scalogram using EEG and ECG-based HRV signals. The model's accuracy and interpretability make it a viable tool for mental health providers to diagnose depression quickly and individually. The study lays the groundwork for mental health diagnostics research and stresses the worldwide impact of AI-based technologies. This work shows that machine learning and deep learning may detect depression patterns in EEG and HRV data early. The model uses MobileNetV2 and AdaBoost and is accurate and interpretable, revealing depression's physiological signs. While there are still issues, this research sets the groundwork for mental health diagnostics and shows how AI-based tools might improve global mental health outcomes.

VI. CONCLUSION

In this study, we introduce depressive-deep, a novel approach for predicting depression using a combination of preprocessed EEG and ECG-based HRV signals. We generated a 2D scalogram by combining ECG and EEG signals. These accurate predictions were made using the MobileNetV2 deep learning architecture and AdaBoost ensemble learning. They were for major depressive state (MDS), cognitive and emotional arousal (CEA), mood disorder patterns (MDPs), mood and emotional regulation (MER), and stress and emotional dysregulation (SED). We made sure the system could be used by anyone by pre-training the depressive-deep model on the MODMA and SWELL-KW datasets and using wearable IoMT devices to collect signals. Rigorous validation through cross-validation and other criteria demonstrated the robustness of our model. With a remarkable 96% accuracy in depression prediction, surpassing previous methods, our approach highlights the potential of machine learning in early depression detection, thereby enhancing mental health diagnosis and treatment outcomes. We require further research and validation to enhance our strategy and guarantee its clinical effectiveness.

Small datasets may limit the model's generalizability, requiring validation on bigger and more diversified datasets. DL models like MobileNetV2 are difficult and require further study to enhance forecast interpretability.

DATA AVAILABILITY STATEMENT

MODMA dataset [36]: https://modma.lzu.edu.cn/data/application/#data_1 (accessed date: 1 January 2023). SWELL-KW dataset [37]: https://cs.ru.nl/~skoldijk/SWELL-KW/Dataset.html (accessed date: 1 January 2023).

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CONFLICTS OF INTEREST

The author declares that there are no conflicts of interest.

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