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RESEARCH ARTICLE

# DepCap: A Smart Healthcare Framework for EEG Based Depression Detection Using Time-Frequency Response and Deep Neural Network

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**ABSTRACT** A novel wearable consumer electronics device for detecting Major Depressive Disorder (MDD) has been developed using deep learning techniques for smart healthcare. Accurate identification of MDD through individual interviews or perceiving Electroencephalogram (EEG) signals is challenging. This study presents the concept of a novel wearable smart cap named DepCap for real-time detection of depression using EEG signals. First, spectrogram images are generated from the EEG signals of depressed and healthy patients using Short-Time Fourier Transform (STFT) to extract valuable features. Then, these spectrogram images obtained from STFT are used as input to the classification model. A deep analysis is done using various neural networks consisting of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). RNNs are used to extract temporal data from the EEG, while CNNs are used to retrieve spatial information. Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) are the two different kinds of RNNs evaluated in this work. The implemented combination models are (STFT+CNN), (STFT+CNN-LSTM) and (STFT+CNN-GRU). Four pre-trained models, Inception, AlexNet, VGG16, and ResNet50 are also implemented along with the combination models. The dataset for this work is a publicly accessible dataset with 33 major depressive disorders and 30 healthy subjects. The evaluation results show that the STFT+CNN-LSTM has much better performance in terms of accuracy, sensitivity, specificity, and precision of 99.9%, 100%, 99.8%, and 99.4%, respectively, than other implemented models. The proposed wearable device DepCap is based on the STFT+CNN+LSTM model and is also integrated with the Internet of Medical Things (IoMT) framework for real-time depression detection.

**INDEX TERMS** Consumer electronics, DepCap, EEG signals, hybrid deep-learning model, MDD, smart healthcare, STFT.

## I. INTRODUCTION

Depression is a neurological disorder that affects about 280 million individuals globally and there are around 700,000 death occurs by suicide each year as a result of depression. The most common symptoms of depression include sadness, loss of interest, low mood, lack of focus, and the worst suicidal ideation [1], [2], [3]. It is a severe psychiatric condition evaluated by a domain expert and treated through psychotherapy and medicine prescription [4]. The manual

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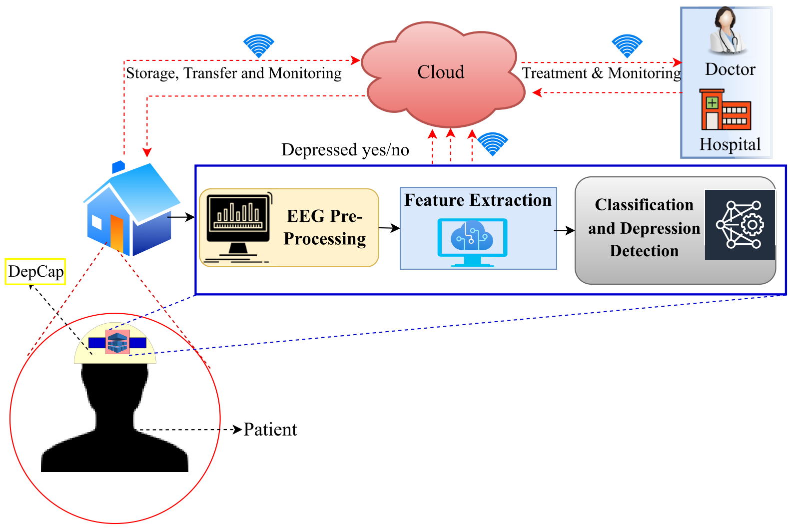


**FIGURE 1.** Framework for automatic depression disorder detection model in real-time.

diagnostic process such as the Beck Depression Inventory, is prone to errors in precise depression detection. Therefore, it is important to develop an effective and automatic depression detection system using a smart healthcare system.

The physiological function of the brain is captured by the EEG signal [5], which can be recorded using various feature extraction techniques. The EEG signal can be used to detect numerous neurological diseases, such as Seizures [6], Schizophrenia [7], [8], [9], [10], Parkinson's [11], Autism [12], Depression [13], [14], Sleep disorders, Anxiety [15], and Alzheimer [16]. Linear approaches may not be suitable for detecting complex dynamic variations in EEG signals. Therefore, the extraction of non-linear features is employed from the EEG signal using machine learning-based approaches [17], [18], [19]. The choice of important features along with a suitable classification approach would be very important to have better accuracy [20]. The extracted features of the EEG signal are further analyzed either in the time or frequency domain for precise depression detection.

The various non-linear methods such as Higher Order Spectra (HOS), Fractural Dimensions (FD), and Hurst Exponent (HE), were investigated in [20] with an accuracy of 98%. In [33], a two-layer artificial neural network model was presented to extract features like Relative Wavelet Energy (RWE) and Sample Entropy. Support Vector Machine (SVM) classifier segregates depressed and control subjects in [22]. The techniques like kernel eigen-filter-bank based patterns [24], SVM [34], and Linear Predictive Coding (LPC) [23] are also used to extract valuable features from EEG. In addition, many scholars have used CNN in previous research employing Electrocardiogram (ECG) signals to detect heart diseases [35], [36].

Traditional healthcare has given way to mobile health, e-health, connected health, and smart health (sHealth) [37]. Patient data is collected through smart sensors to receive real-time assistance from a healthcare provider at a remote location. The IoMT has transformed smart healthcare solutions with high-quality care and accurate diagnosis [38]. The critical condition of a patient can be accessed and monitored in real-time for quick action, which is helpful in doing health analysis and determining depression status. In this paper, a concept of smart wearable EEG-based DepCap for real-time depression detection is developed. The framework for the same is depicted in Figure. 1. This framework is divided into four main parts:

- EEG data is continuously recorded from the patient with the help of a proposed wearable device known as DepCap and then, this recorded data is pre-processed for the machine learning model. Here, the EEG from publicly available dataset [22] is preprocessed and fed into the DepCap model due to the unavailability of real-time EEG.
- Electrodes installed in the DepCap are used to acquire EEG data. Then, the EEG signal is subjected to data pre-processing such as artifact removal, feature extraction, and classification for MDD detection. For feature extraction, time-frequency domain information is retrieved from EEG using STFT, and the spectrogram images are produced. Further, the classification of spectrogram images is done through hybrid CNN-LSTM architecture. The publicly available data set [22] with 33 major depressive disorders and 30 healthy subjects is used in this work. The proposed hybrid model of STFT+CNN-LSTM provides efficient automatic depression detection with modest computational implementation.
- The status of two LEDs attached to DepCap can detect if a person is suffering from depression or not.
- The status of the patient is stored on the cloud through IoMT and can be used by doctors and researchers for further treatment. Here, the google cloud platform is used to store and manage the classified output, which

**TABLE 1. Summary of preceding methods on MDD using EEG.**

| Author, Year | Subjects | Used Method | Accuracy(%) |
|---|---|---|---|
| Bairy et al. [21], 2016 | 15 Control, 15 Depressed | DWT+SVMRBF | 88.92 |
| Mumtaz et al. [22], 2017 | 30 Control, 33 Depressed | Power features+SVM | 98.4 |
| Bairy et al. [23], 2017 | 15 Control, 15 Depressed | Spectra features+Bagged tree | 94.30 |
| Liao et al. [24], 2017 | 20 Control, 20 Depressed | Kernel eigen filter bank+SVM | 81.23 |
| Acharya et al. [25], 2018 | 15 Control, 15 Depressed | CNN | 93.54 |
| Ay et al. [26], 2019 | 15 Control, 15 Depressed | CNN-LSTM | 97.66 |
| Li et al. [27], 2019 | 27 Control, 24 Depressed | ConvNet | 85.62 |
| Wan et al. [28], 2020 | 12 Control, 23 Depressed | HybridEEGNet | 79.08 |
| Sharma et al. [29], 2021 | 24 Control, 21 Depressed | CNN-LSTM | 99.10 |
| Sharma et al. [30], 2021 | 30 Control, 34 Depressed | Non-linear features+SVMRBF | 98.9 |
| Chao et al. [31], 2021 | 14 Control, 16 Depressed | Spatial pattern | 84 |
| Loh et al. [32], 2022 | 30 Control, 34 Depressed | CNN | 99.58 |
| Present work, 2022 | 30 Control, 34 Depressed | STFT+CNN-LSTM | 99.58 |

can be accessed for future reference. As a result, it offers a conclusive, closed-loop approach to the diagnosis and treatment of depression.

The paper is structured as follows: In Section II prior research work based on depression detection using EEG signals, along with the novel contribution of this research, is presented. Section III discussed the data set used for this research and various deep learning models such as STFT, CNN, LSTM, and GRU. Section IV presents the detailed architecture of the proposed consumer electronics device DepCap for depression detection. Then, Section V describes the outcomes of the proposed model, and results are compared with other studies on the same dataset. Section VI, the final section, describes the conclusion and future work.

## II. RELATED WORK

The present section covers the study of depression detection with the help of EEG and includes detailed literature on consumer products for depression detection.

### A. DEPRESSION DETECTION USING EEG

Several methods for MDD detection using EEG signals have been proposed in the literature as given in Table 1. An Accuracy of 98.4% was achieved using EEG alpha inter-hemispheric asymmetry and power of multiple frequency bands as input factors to distinguish between people with MDD and healthy subjects [22]. Depressed signals are identified from typical EEG signals with an accuracy of 94.30% using LPC residual algorithms in [23]. A powerful Kernel Eigen-Filter-Bank Common Spatial Pattern (KEFB-CSP) is employed for the EEG feature extractor in [24]. CNN-based models are implemented in [25] and [32] to detect depression with an accuracy of 93.54% and 99.59%, respectively. Hybrid deep-learning-based models integrating CNN and LSTM architectures are presented in [26], [29] to analyze EEG signals and identify depression. A new network called HybridEEGNet is proposed in [28] consisting of two parallel and independent CNN models with an accuracy of 79.08%. A combination of non-linear features and SVMRBF is explored in [30] for depression detection with an accuracy of 98.90%. A hybrid CNN-Temporal-Convolutional Neural Network (TCN) model is proposed in [40] for continuous estimation of depression score based on the Beck depression inventory test and reported the mean absolute error (MAE) of 1.73. An EEG-based depression detection method using spatial information is proposed and reported an accuracy of 84% in [31]. A novel clustering method is proposed in [41], which shows the topological difference in the brain of depressed and healthy subjects.

### B. CONSUMER ELECTRONICS FOR DEPRESSION DETECTION

There are numerous tools for detecting physical diseases in humans, but there are few tools to determine a person's mental state. The acquisition and storage of biosignals with high accuracy is the crucial component of smart healthcare and the IoMT-based applications [42]. Over the past ten years, portable consumer electronics devices have presented a new research perspective in the field of the Internet of Wearable Devices. Consumer electronics devices have integrated numerous biosignals such as Photoplethysmograph (PPG), EEG, and Electrocardiograph (ECG) for immediate monitoring of diseases. Many smart wearable devices are being developed that can measure various elements of health without being intrusive. A smart wearable device based on ECG was proposed for the monitoring of arrhythmia disorders [43].

The monitoring of cardiovascular diseases using an ECG was logically studied using a wireless sensor network [44]. A wearable device for fast seizure detection using EEG has been proposed in [39] has enormous seizure-revealing latency. Another EEG-based consumer electronics device eSeiz [6] has better latency performance. Although it was discovered that certain EEG characteristics may primarily predict depression, however, there are not many studies

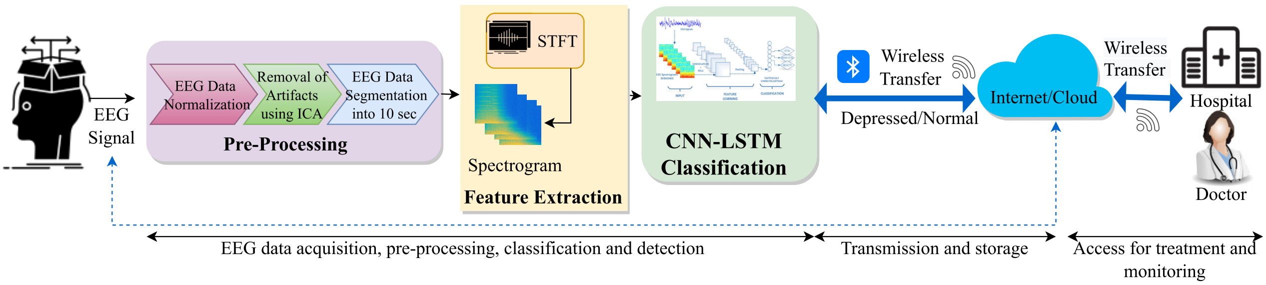


**FIGURE 2.** Block diagram of the proposed depression detection system (DepCap).

**TABLE 2.** Literature based on existing consumer electronics using EEG.

| Existing Work | Biosignal | Method Used | Latency |
|---|---|---|---|
| Seizure Detection Gadget [39] | EEG | Hjorth Parameter, DNN | - |
| Seizure Detection Gadget [6] | EEG | Hyber synchronous pulses, SRA | High Latency |
| DepCap (Proposed Work) | EEG | Spectrogram+CNN-LSTM | Very Low Latency |

to design for real-time depression using smart healthcare devices. In this paper, a smart wearable device named DepCap is proposed to detect whether a person has depression or not as shown in Figure. 2. DepCap consists of electrodes that capture EEG signals from the brain. The signals are then processed in an algorithm based on a machine-learning model. The hybrid (STFT+CNN), (STFT+CNN-LSTM), (STFT+CNN-GRU) models are implemented in this work to detect depression from EEG signals with high accuracy. Some consumer electronics healthcare gadgets are listed in Table 2.

### C. NOVEL CONTRIBUTION

- The new hybrid CNN-LSTM/GRU model is proposed utilizing spectrogram images generated with the help of STFT of EEG.
- The proposed portable device DepCap has been developed through a smart-healthcare framework with high accuracy and integrated with the IoMT framework. A person's condition can be diagnosed and monitored remotely using DepCap.
- The proposed depression detection system is accurate, robust, and reliable for real-time depression detection.
- The model has been able to detect the depression precisely with lesser complexity in comparison to existing machine learning models

## III. PROPOSED SMART HEALTHCARE FRAMEWORK FOR DEPRESSION DETECTION

### A. DATA AND ITS PRE-PROCESSING

This study uses the reference database provided by [22], which was assimilated at the Hospital Universiti Sains Malaysia (HUSM). For this data set, 64 participants (24 Female, 40 Male) were selected from two groups, with the average age ranging from 12 to 77 years. The mean age and standard deviation of the 34 MDD patients were 40.33 and 12.861 years, respectively. The additional study set comprised 30 healthy participants, with a mean age of 38.227 and a standard deviation of 15.64. The MDD patients have been diagnosed with MDD via the Diagnostic and Statistical Manual IV (DSM-IV). An ethics committee approved the study design, and all subjects signed the consent form to participate. The international 10-20 electrode placement standard was used to position the EEG sensors on the scalp. Each Participant's EEG was recorded for 10 minutes, comprising 5 minutes with their Eyes Open (EO) and 5 minutes with Eyes Closed (EC). The frontal, temporal, parietal, occipital, and central regions on the scalp are covered by the placement of 19 electrodes comprising Fp1, Fp2, F3, F4, F7, F8, Fz, T3, T4, T5, T6, P3, P4, Pz, O1, O2, C3, C4, and Cz. The EEG signals of a healthy and MDD patient are shown in the Figure. 3, which shows the frequent occurrence of casual slowing and choppy activities in depressed EEG. A Butterworth band pass filter of cut-off frequency 0.5Hz-70Hz and a notch filter of 50Hz is used to remove the power grid effect [45], [46] is used as a part of pre-processing. Independent Component Analysis (ICA) is used to reduce artifacts caused by patient movement and eye blinking. Then, the whole EEG signal of 5 min duration is segmented into the interval of 10s. Finally, the Z score normalization technique is used for amplitude scaling of each EEG segment before being sent to the proposed neural network.

### B. OUR VISION OF EEG-BASED DEPRESSION DETECTION

A hybrid deep CNN-LSTM/GRU model is designed to detect depression disorder using EEG spectrogram images. Extraction of time-frequency-based features using STFT of EEG is the crucial factor of this study. In the proposed model, LSTM/GRU block performs sequence learning while CNN handles feature extraction, selection, and classification.

#### 1) STFT

As EEG is a time-varying signal, the Fourier Transform (FT) fails to record the variations in amplitude and frequency

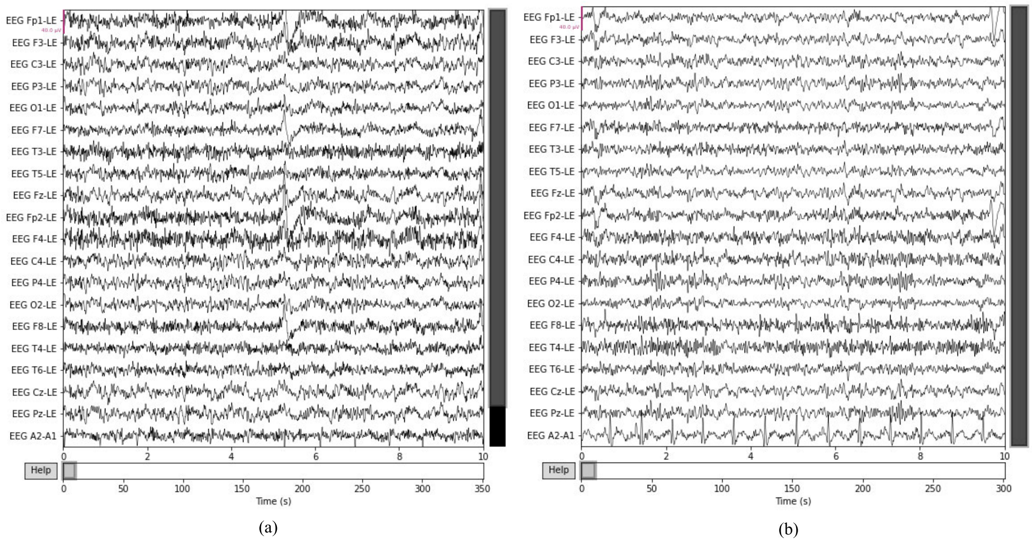


**FIGURE 3.** **EEG signals of (a) Healthy subject and (b) Depressed subject.**

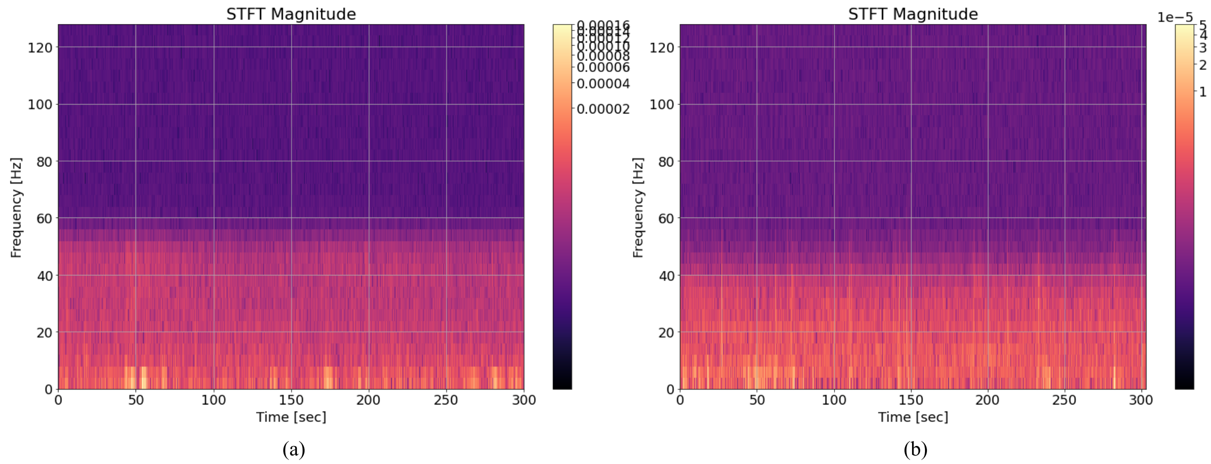


**FIGURE 4.** **Spectrogram images (Time-Frequency Response) produced from STFT for (a) Healthy and (b) Depressed EEG.**

over time. It examines the frequency data averaged over the period. Here EEG signals are administered for depression using STFT to generate a feature map from EEG. STFT is an extension of simple Fourier transform, that leads to better spectral analysis to extract features and detect abnormalities in EEG signals at every instant [47]. STFT coefficients are derived after dividing the signal into smaller segments with a sliding window in the time domain. The time-frequency graph obtained by STFT is called a spectrogram, providing good resolution due to time-frequency localization. The spectrogram images obtained from STFT of filtered EEG of depressed and healthy subjects are shown in the Figure. 4. Mathematically STFT can be defined as given in Eq. (1) below

$$S(r, w) = \sum_{s=-\infty}^{\infty} x(s)w(r-s)\exp(-\iota\omega r) \tag{1}$$

where x(s)w(r-s) is the window-time section of input x(s) of frequency k and at time r. Further, STFT coefficients can be expressed as eq. (2)

$$S(r, k) = |S(r, \omega)|_{\omega=2\Pi k/N} \tag{2}$$

where N is the total number of discrete frequencies. In time-frequency representation, the EEG spectrogram image can be expressed as given by eq. (3)

$$Spec(r, k) = |S(r, k)|^2 \tag{3}$$

In this work, a hamming window of varied window size between 0.2 to 1 second is used for achieving optimum results. After this, the frequency over time graph can be produced easily.

### 2) CNN

CNN is a Deep Neural Network that can identify and classify certain features from the biological image [48], [49]. The CNN consists of three layers where the first layer performs feature extraction using various linear and non-linear functions. The second layer is the pooling layer which performs

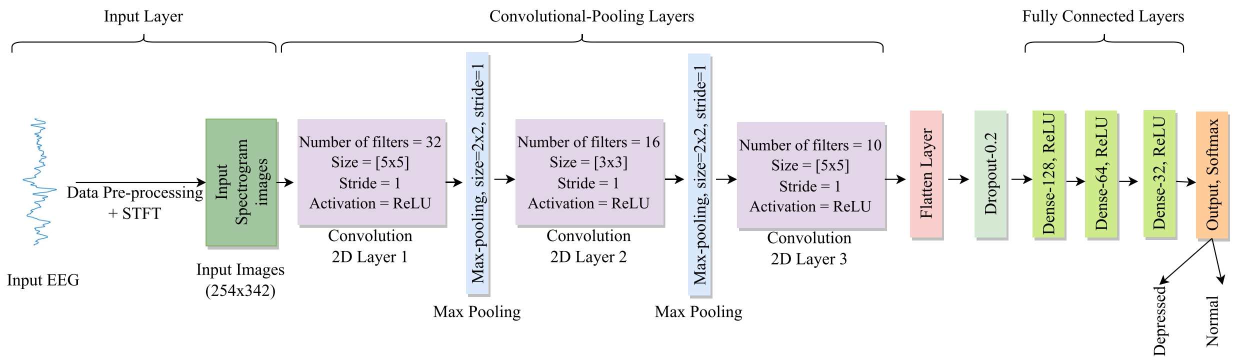


**FIGURE 5.** Implementation of CNN-based depression disorder detection system.

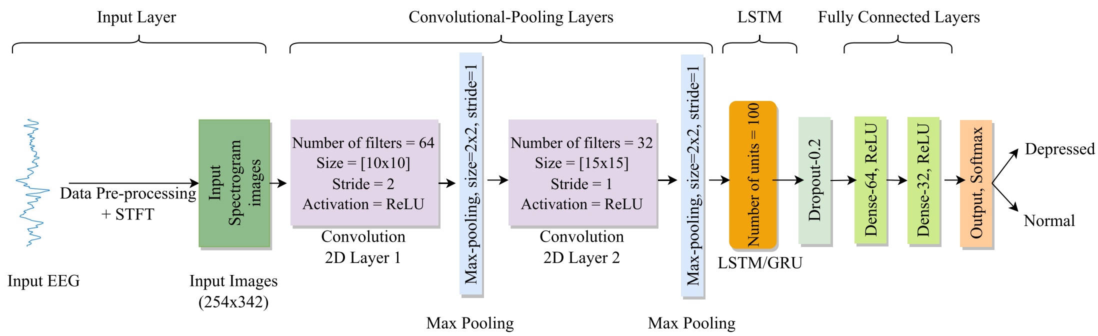


**FIGURE 6.** Implementation of CNN-LSTM, CNN-GRU based depression disorder detection system.

the downsampling process and moderates the dimension of the feature map. The final layer is the dense layer, which flattens the previous layer's output into a single vector. Numerous parameters, including kernel size, number of filters, and stride, must be appropriately calibrated for effective network architecture. The convolution network is described mathematically as Eq. (4)

$$F(t) = (E^{*}w)(t) = \int_{-\infty}^{\infty} E(b)w(t-b)db. \tag{4}$$

where E is the input EEG data and F defines the feature map. CNNs can make the system more complex and slow, but these networks have become increasingly popular for models involving large datasets. These networks are preferred over traditional machine learning methods for several reasons: 1) CNNs can learn a high-level representation of data directly from the input, unlike other machine learning algorithms requiring hand-crafted features. 2) CNNs use convolutional filters, which are very efficient in extracting spatial information which other machine-learning models can miss. 3) CNNs can be trained more efficiently on larger datasets than other machine learning models. 4) CNNs can be optimized for speed and complexity by altering various parameters and fortifying the network's architecture.

### 3) RNN

Sequential learning of signals can be achieved by deep learning networks such as LSTM [50], [51] and GRU which are two different types of RNNs. The declining gradient is a difficulty for RNN networks. Therefore, it cannot be used for long-term dependencies. LSTM consists of memory cells, which help in storing and recalling previous input over a long period of time. Four distinct functions, including hyperbolic tangent (tanh), sigmoid ($\sigma$), multiplication (x), and sum (+), are included in the LSTM unit, which makes it simpler to update the weight during the backpropagation process. Mathematically LSTM can be restricted as given below from Eq. (5) to Eq. (11)

$$n_t = \tanh(Wt_n[s_{t-1}, q_t] + bt_n) \tag{5}$$
$$i_{gt} = \sigma(W_{ig}[s_{t-1}, q_t] + bt_{ig}) \tag{6}$$
$$f_{gt} = \sigma(W_{fg}[s_{t-1}, q_t] + bt_{fg}) \tag{7}$$
$$ls_t = ls_{t-1}fg_t + n_t ig_t \tag{8}$$
$$Us_t = \tanh(Wt_{us}ls_{t-1}fg_t + bt_{us}) \tag{9}$$
$$Us_t = \tanh(Wt_{us}ls_{t-1}fg_t + bt_{us}) \tag{10}$$
$$Vs_t = \sigma(Wt_{vs}[s_{t-1}, q_t] + bt_{vs}) \tag{11}$$

Let there be Q local features, $q_1, q_2 \ldots q_Q$, extracted from the CNN model. $q_t$ is input signal feature, $s_{(t-1)}$, $ls_{(t-1)}$ are short and long term memory values, $bt_n$ is bias, $Wt_n$ defines the weight matrix, $fg_t$, $ig_t$ are forget and ignore factor, $s_t ig_t$, $ls_{(t-1)}fg_t$, $ls_t$, $Us_t Vs_t$ are outputs of different gates.

GRU, an alternative to LSTM, is a different class of RNNs. Unlike LSTM, which has three gates (input, output, and forget), GRU only has reset and update gates. As GRU does not have an output gate, it gives the stored memory output directly, unlike LSTM, which can decide which output to select or discard.

## IV. DepCap: PROPOSED WEARABLE DEVICE FOR REAL-TIME DEPRESSION DETECTION

In this work, three deep learning models (STFT+CNN), (STFT+CNN-LSTM), and (STFT+CNN-GRU) are implemented and analyzed to develop a smart depression detector named DepCap. All the essential parameters, including many layers, filters, and other parameters, are selected after extensive experimental analysis by varying parameter settings.

### A. PROPOSED HYBRID MODEL-1 USING STFT+CNN

The CNN model implemented in this work consists of 3 convolution layers, two max-pooling layers, three dense layers, 1 flatten layer, 1 dropout layer, and softmax at the end, as shown in Figure. 5. In the designed model, the input layer contains an EEG spectrogram image with dimensions ($254\times342\times3$), (height, width, RGB three-color channel). It is convolved with 32 filters of size $5\times5$ and a stride of 1 to create a feature map. The second convolution layer has 16 filters of size $3\times3$, while the third layer has ten filters of size $3\times3$. The convolution layer can be considered as an array of filters to extract features from spectrogram images. ReLU, a rectified linear unit, is used as an activation function with each CNN layer. The pooling layer performs downsampling with filter size of $2 \times 2$ and a stride of 1 to reduce the input size. The sixth layer is the dropout layer, with a dropout rate of 0.6 to elude overfitting. The three dense layers are used, followed by flattened and dropout layers consisting of 128, 64, and 32 neurons. The last layer ends up with two classes, depressed and non-depressed. Softmax is an activation function that normalizes the output of all dense layers. In this study, there are two possible outcomes (depressed or non-depressed); therefore, two neurons are needed to express them.

### B. PROPOSED HYBRID MODEL-2 USING STFT+CNN-LSTM/GRU

The CNN model merely iterates through the input in various intermediate hidden layers. However, the output can not be returned to the network. Therefore, CNN algorithms are excellent at capturing temporal features but weak at learning sequential information. This research proposes a hybrid approach that combines CNN and LSTM to solve this problem. The architecture of the proposed hybrid deep network STFT+ CNN-LSTM/GRU is shown in Figure 6. The STFT+CNN-LSTM/GRU model includes two convolution layers. 64 and 32 filters of size ($10 \times 10$), and ($15 \times 15$) respectively are used for each convolution layer. These filters are convolved with the input EEG spectrogram images to yield output feature maps. A ReLU function is used after each convolution layer to add non-linearity. The LSTM/GRU is used for sequence learning after max–pooling layer. Dense layers, including 64 and 32 neurons, respectively categorize healthy and depressed patients.

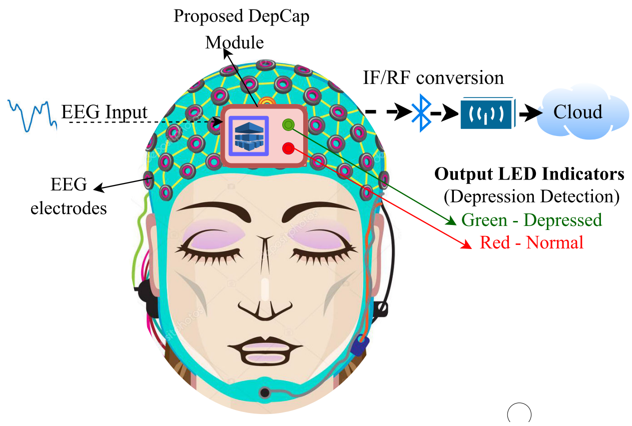


**FIGURE 7. Schematic of proposed DepCap.**

### C. PRE-TRAINED MODELS

Several pre-trained CNN models have been implemented and proposed in the literature for many machine learning-based applications. Some of them are Xception, VGG16, Inception, AlexNet, and ResNet. These models have shown exemplary performance in feature extraction and classification of image data. In this work, four well-known pre-trained CNN networks, VGG16, Inception, AlexNet, and ResNet50, are also implemented to classify spectrogram images for depression detection. A detailed description of all these models can be found in [52]. These existing CNN networks are highly complex with many learnable hyperparameters, but better accuracy can also be achieved by varying the number of layers, filter size, dropout, etc. Therefore, three configurable deep learning models are implemented in this work wherein different parameters are selected after an extensive literature review and experiments.

### D. DepCap: A NOVEL CONSUMER ELECTRONICS WEARABLE CAP FOR REAL-TIME DETECTION OF DEPRESSION FROM EEG SIGNALS

A portable consumer electronics wearable device concept called the DepCap is proposed in this study for the rapid diagnosis of depression. Figure. 7 illustrates the proposed design for the DepCap, which is in the form of a hood that includes electrodes, a display unit consisting of Red and Green LED, an Edge Processing Unit (EPU), and communication components. A hybrid (STFT+CNN-LSTM) model which has been trained to detect depression disorder and reported the best accuracy is used in this DepCap module. The flowchart of the proposed algorithm for detecting depression disorder using DepCap is shown in Figure. 8. The LED unit displays the depression status of the subjects in real-time. When depression is detected, physicians and other caretakers of the patient are alerted. In addition, the EEG data are persistently stored in the cloud for the forthcoming patient examination, supporting the anticipated structure's success. The potential of DepCap as a depression detection gadget for the general consumer market is optimistic. The patient's EEG signal is first analyzed by the EPU, which detects the

**TABLE 3. Parameter settings used to generate the model.**

| Parameter | Value |
|---|---|
| Batch Size | 128 |
| Optimizer | ADAM |
| Loss | Categorical cross entropy |
| Output Metric | Accuracy, specification, sensitivity, precision |
| Learning rate | 0.0001 |
| Epochs | 50 |

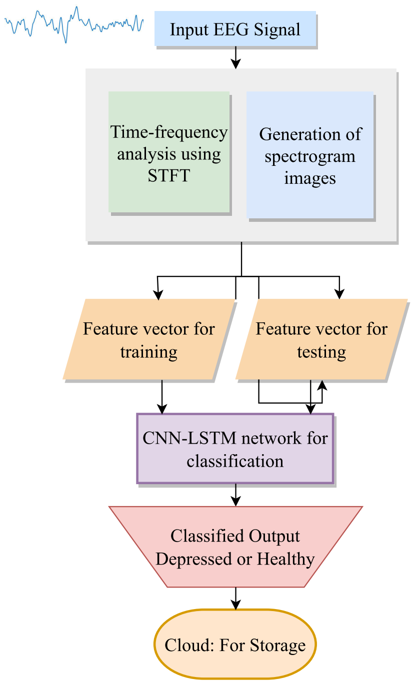


**FIGURE 8. Flow chart of the proposed algorithm.**

depression disorder. The acquired data and its analysis are stored in the cloud to improve model training and for future reference. LED sights a cautionary indication in response to analysis of the EEG signal. This edge data processing is particularly effective since more data are being produced at the user edge of the network. The other crucial characteristics of this recommended DepCap are high accuracy, affordability, portability, and low latency.

## V. RESULT AND DISCUSSION

In this work, an automated depression detection system DepCap is proposed wherein pre-processed 1D EEG is first converted into 2D spectrogram images using STFT. Here, a medium size Kaiser window of size $2^n - 1$ is used for windowing, where n is the number of bits. The spectrogram image obtained from STFT is fed to configured deep networks: CNN, CNN-LSTM, and CNN-GRU. The spectrogram images are also fed to pre-trained VGG16, Inception, AlexNet, and ResNet50 networks for better performance comparison.

### A. ENVIRONMENT SET-UP

Google Colab and the Keras framework are used to train and test deep learning models. The model is designed using Python 3.8.1. The suggested network is trained for 50 epochs. The data is shuffled for each epoch and accuracy is calculated. The training of the model is done with a batch size of 128, ADAM (Adaptive Moment Estimation) optimizer is used to improve the training efficiency, and an initial learning rate of .0001 is used. Table 3 lists the various parameter settings used to build the model.

### B. PERFORMANCE MEASUREMENT

To develop meaningful features from the dataset, a confusion matrix is created and the parameters such as accuracy, specificity, precision, and sensitivity are obtained from the confusion matrix. The sensitivity of a test is its ability to identify a subject as positive who has the disease. On the contrary, the specificity of a test is its ability to identify a subject as negative who does not have the disease.

$$Acc(\%) = [(T_{pt} + T_{nt})/(T_{nt} + T_{pt} + F_{nt} + F_{pt})] * 100 \tag{12}$$

$$Sv(\%) = [T_{nt}/(T_{nt} + F_{pt})] * 100 \tag{13}$$

$$Ps(\%) = [T_{pt}/(T_{pt} + F_{pt})] * 100 \tag{14}$$

$$Sy(\%) = [T_{pt}/(T_{pt} + F_{nt})] * 100 \tag{15}$$

There are two output classes: Depressed and Normal
$T_{pt}$ (True Positive): Normal spectrograms classified as Normal, $T_{nt}$( True Negative): Normal spectrograms classified as Depressed, $F_{nt}$(False Negative): Depressed spectrograms classified as Depressed, $F_{pt}$(False Positive): Depressed spectrograms classified as Normal. All proposed and pre-trained models are evaluated based on performance metrics, including accuracy, specificity, precision, and sensitivity employing a 10-fold cross-validation approach on an EEG MDD dataset. The same results are reported in Table 4. It can be concluded from Table 4 that using the database provided in [22], the performance of the proposed STFT+CNN-LSTM in terms of accuracy, sensitivity, specificity, and precision of 99.9%, 100%, 99.8%, and 99.4% is superior when compared to other models using the same dataset. A parameter comparison of all the implemented models is also given in Table 5. VGG16 is a 16-layer network consisting of 13 convolution layers, three fully connected layers, a filter size of 3, and a stride of 1. It has 138 million learnable parameters and reports an accuracy of 96.22%. Inception is a 22-layer network consisting of convolution, inception, and fully connected layers with a filter size of 1, 3, and 5. It has around 6.5 million trainable parameters and produces an accuracy of 97.00%. AlexNet is an 8-layer network with five convolution layers, three fully connected layers, and filters of sizes 3, 5, and 11. It has 62 million learnable parameters and reports an accuracy of 94.98%. ResNet50 is a 51-layer network with

**TABLE 4.** Performance comparison of different implemented models.

| Parameters | VGG16 | AlexNet | Inception | ResNet50 | CNN | CNN-LSTM | CNN-GRU |
|---|---|---|---|---|---|---|---|
| Accuracy(%) | 96.22 | 94.98 | 97.00 | 97.32 | 99.10 | 99.9 | 99.84 |
| Sensitivity(%) | 95.00 | 92.89 | 98.1 | 97.93 | 98.73 | 100 | 100 |
| Specificity(%) | 96.98 | 94.90 | 97.32 | 98.50 | 99.36 | 99.81 | 99.57 |
| Precision(%) | 94.69 | 95.10 | 96.55 | 96.79 | 98.98 | 99.47 | 99.23 |

**TABLE 5.** Model parameter comparison for different implemented networks.

| Parameters | VGG16 | AlexNet | Inception | ResNet50 | CNN | CNN-LSTM | CNN-GRU |
|---|---|---|---|---|---|---|---|
| Convolution Layers | 13 | 5 | 9 inception layers+3 convolution layers | 50 | 3 | 2 | 2 |
| Fully Connected Layers | 3 | 3 | 1 | 1 | 3 | 2 | 2 |
| Learnable Parameters | 138M | 62M | 6.5M | 25M | 0.63M | 0.89M | 0.81M |
| Filter Size | 3 | 3, 5, 11 | 1, 3, 5 | 1, 3, 7 | 3, 5, 5 | 10, 15 | 10, 15 |
| Accuracy(%) | 96.22 | 94.98 | 97.00 | 97.32 | 99.10 | 99.9 | 99.84 |

**TABLE 6.** Accuracy comparison of proposed STFT+CNN-LSTM model with addition of different SNR.

| SNR(dB) | Accuracy(%) |
|---|---|
| 0 | 99.90 |
| 10 | 97.76 |
| 20 | 97.92 |
| 30 | 98.01 |
| 40 | 98.57 |
| 50 | 99.21 |

50 convolution layers and one fully connected layer, and it has around 25 million learnable parameters. It gives an accuracy of 97.32%. It is also evident from Table 5 that the complexity of proposed CNN, CNN-LSTM, and CNN-GRU models has significantly reduced with only 0.63 million, 0.89 million, and 0.81 million learnable parameters. The total training time of CNN, CNN-LSTM, and CNN-GRU networks is 2356s, 3190s, and 3343s, respectively. The model parameters of the configured networks are selected after examining the training and testing curves to avoid overfitting and trial-error methods. The reliability and robustness of the proposed CNN-LSTM model are also examined by adding white noises of different SNRs ( 0, 10, 20, 30, 40, and 50 dB). It can be seen from Table 6 that the differences in the accuracy results of all the SNRs for the proposed model are small.

Table 7 summarizes a comparison between the proposed approach and other approaches available in the literature. Statistical analysis was also performed for the accuracy comparison using two-factor ANOVA (without replication) and t-test with a 95% confidence level. The results show that the accuracy results of STFT+CNN-LSTM and STFT+CNN-GRU models are not significantly different ($p>0.05$). The results also conclude that STFT+CNN-LSTM/GRU outperformed other implemented models in terms of accuracy in pairwise comparisons (with $p<0.05$). The performance of various evaluation parameters of the proposed model is compared with recent models with the same dataset.

The MeDep model [55] uses melamine patterns and neighborhood component analysis to extract the features from the EEG signals to detect MDD. Melamine patterns, multilevel discrete wavelet transform, and statistical features are utilized to extract features to achieve high classification accuracy. NCA then selects the top 256 features for classification using kNN or SVM classifiers. The model offers an accuracy of 99.14% at the cost of the computational complexity of the model with 10-fold cross-validation.

BioDep [57] proposed a 2D-CNN network for detecting depression disorder. Wavelet coherence is used to analyze default mode networks in the brain. The model comprises of 5 CNN layers with a filter size of $5 \times 5$ for all layers, normalization layer, ReLU, global average pooling layer, dropout layer, dense layers, and Softmax layer. As the number of layers increases training time of the model rises. The model's accuracy, sensitivity, and specificity are 98.1%, 98.0%, and 98.2%, respectively. DepML [56] concentrates on a technique for identifying pertinent features (linear and non-linear) and efficient classifiers (logistic regression, RBF-SVM, K- nearest neighbor, decision tree, and naïve Bayes) that can reliably distinguish healthy and depressed individuals.

StDep [32] is the most widely used association model since it employs CNN and STFT techniques. The model uses two convolution layers of 32 filters of size $3 \times 3$, two layers of dropout and dense, and one layer of max pool and flatten. The drawbacks of the model are its high computational memory requirement and lengthy training period. The network's attained accuracy, precision, sensitivity, and specificity with 10-fold cross-validation are 99.58%, 99.40%, 99.70%, 99.48%, and 99.55%, respectively.

**TABLE 7.** Comparison between the proposed depression detection system and others proposed in the literature using the same dataset. (Best results are highlighted).

| Author/Year | Method used | Number of participants | Accuracy (%) | Sensitivity (%) | Specificity (%) | Precision (%) |
|---|---|---|---|---|---|---|
| Mumtaz et al. [22], 2017 | Power and symmetry features+SVM | 30 Normal, 34 Depressed | 98.4 | 96.66 | 100 | - |
| Mahato et al. [53], 2019 | Alpha power+RWE+MLPNN | 30 Normal, 34 Depressed | 93.33 | 94.44 | 87.78 | - |
| Kang et al. [54], 2020 | Asymmetry image+2D-CNN | 30 Normal, 34 Depressed | 98.8 | 99.1 | 98.5 | - |
| Aydemir et al. [55], 2021 | Melamine pattern+SVM | 30 Normal, 34 Depressed | 99.1 | 98.4 | 99.8 | 99.8 |
| Sharma et al. [56], 2022 | Non-linear features+RBFSVM | 30 Normal, 34 Depressed | 98.9 | 99.2 | 99.7 | - |
| Khan et al. [57], 2022 | Wavelet coherence | 30 Normal, 34 Depressed | 98.1 | 98.0 | 99.82 | - |
| Loh et al. [32], 2022 | CNN | 30 Normal, 34 Depressed | 99.58 | 99.70 | 99.48 | 99.40 |
| Implemented Model 1, 2022 | STFT+VGG16 | 30 Normal, 34 Depressed | 96.22 | 95.00 | 96.98 | 94.69 |
| Implemented Model 2, 2022 | STFT+AlexNet | 30 Normal, 34 Depressed | 94.98 | 92.89 | 94.90 | 95.10 |
| Implemented Model 3, 2022 | STFT+Inception | 30 Normal, 34 Depressed | 97.00 | 98.1 | 97.32 | 96.55 |
| Implemented Model 4, 2022 | STFT+ResNet50 | 30 Normal, 34 Depressed | 97.32 | 97.93 | 98.50 | 96.79 |
| Implemented Model 5, 2022 | STFT+CNN | 30 Normal, 34 Depressed | 99.10 | 98.73 | 99.36 | 98.98 |
| Implemented Model 6, 2022 | STFT+CNN-GRU | 30 Normal, 34 Depressed | 99.84 | 100 | 99.57 | 99.23 |
| Proposed Model | STFT+CNN-LSTM | 30 Normal, 34 Depressed | 99.9 | 100 | 99.81 | 99.47 |

## VI. CONCLUSION AND FUTURE WORK

This paper proposes the DepCap, a novel concept of a wearable consumer electronics device that automatically diagnoses depression in real time using EEG signals. Three hybrid deep learning models, i.e. (STFT+CNN), (STFT+CNN+LSTM), and (STFT+CNN+GRU) are implemented in this work. Four pre-trained CNN networks, VGG 16, Inception, AlexNet, and ResNet50, are also implemented with spectrogram image as input. DepCap is a wearable device to detect the status of depression in an individual using a smart healthcare system. It provides a closed-loop solution for diagnosing and treating depression disorders using the IoMT framework. The time-frequency representation (spectrogram) of EEG signals is achieved using STFT. The spectrogram images are then processed in a neural network consisting of CNN and LSTM/GRU. The CNN is used for its exceptional feature extraction proficiency in conjunction with LSTM/GRU for long sequence processing. The proposed model is built using EEG signals of the standard data set (33 major depressive disorders and 30 healthy subjects) given in [22]. This research results successfully outpace other methods in detecting depression with the accuracy, sensitivity, specificity, and precision of 99.9%, 100%, 99.8%, and 99.4%, respectively, with 10-fold cross-validation. Future work can be done to improve the training and results of the model with additional data sets of different settings. The model can be enhanced to detect the different phases and stages of depression. The performance of the proposed model can be validated using multiple datasets for performance evaluation.

## APPENDIX

## NOMENCLATURE

The main nomenclature used in this paper is in alphabetical order as given below:

| Nomenclature | Full Form |
|---|---|
| **CNN** | Convolutional Neural Network |
| **EEG** | Electroencephalography |
| **GRU** | Gated Recurrent Unit |
| **LSTM** | Long Short-Term Memory |
| **MDD** | Major Depressive Disorder |
| **MAE** | Mean Absolute Error |
| **RNN** | Recurrent Neural Network |
| **STFT** | Short-Time Fourier Transform |
| **SVM** | Support Vector Machine |
| **TCN** | Temporal Neural Network |

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