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ENHANCING BRAIN-MACHINE INTERFACE APPLICATIONS FOR DISABLED INDIVIDUALS USING VISUAL EVOKED POTENTIALS AND EXPLAINABLE AI

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ABSTRACT

Individuals with severe physical disabilities often rely on Brain Machine Interfaces (BMI) to interact with their environment and regain some level of independence. One promising approach for BMI control in the use of Visual Evoked Potentials (VEP), which are electrical signals created in the brain in response to visual stimuli. However, the interpretation of VEP signals, is complex, presenting a barrier to the widespread adoption of VEP based BMIs. Therefore, in this study, a comprehensive model is proposed to boost the performance of VEP-based BMIs through the incorporation of advanced signal processing techniques and explainable Artificial Intelligence (AI) methods. The pre-processing of Electroencephalogram (EEG) signals plays a vital part in optimizing the performance of VEP based BMIs. To achieve this, an Orthogonal Wavelet Filter is employed, which offers extraordinary flexibility in managing the conservation of appropriate emotional data and the diminution of annoying interference. Next, to captivate the time-frequency representations of EEG signals, the Empirical Mode Decomposition (EMD) based Feature Extraction approach is used, which provides a data-driven approach to decay EEG signals into Intrinsic Mode Functions (IMFs), allowing for the extraction of relevant features related to brain activity. For prediction tasks, such as classifying intended movements or commands from EEG signals, a Modified Recurrent Neural Network with Long Short-Term Memory (RNN-LSTM) classifier is employed. The hyper parameters of the Modified RNN-LSTM model are tuned by employing Chaotic Bat Optimization (CBO), which effectively explores the hyperparameter space and optimizes model performance with rapid computational time. The approach is implemented through the python software and the performance metrics such as classification accuracy, recall, precision, and F1 score are compared with the traditional approaches to evaluate the effectiveness of the methodology. From the obtained outcomes, it is evident that the proposed Modified RNN-LSTM approach achieves high accuracy of (96%), thereby enhancing the daily functioning of disabled individuals.



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I. INTRODUCTION

Severe neurological and cognitive problems have the potential to damage the brain's communication and control routes with its surroundings. Patients who are severely affected possible to miss all voluntary muscular control, containing the capability to move their eyes, and they become totally immobilized in their bodies, unable to speak in any way. The term "locked-in syndrome" is occasionally used to describe this group of severe illnesses, denoting the incapacity to communicate with or show any intention to the world [1]. Giving the brain a novel, non-muscular channel for communication and control a direct BMI to transmit commands and messages to the outdoor environment would help restore functions and overcome limitations. It is a helpful tool for paralysis patients who struggle to communicate their emotions and ideas through their movements [2–5]. Because of its information transfer rate is high and minimal need for user training, VEP-based BMI systems are frequently employed [6–7].

Functional magnetic resonance imaging, functional near-infrared spectroscopy and EEG are tools employed to measure neuronal activities. The functional EEGs have drawn a lot of research attention because they offer a high temporal resolution and non-invasive monitoring capability for recording information about neuronal responses [8–10]. The Preprocessing of EEG signals plays a vital part in optimizing the performance of VEP based BMIs, which seeks to streamline further processing steps while preserving pertinent data [11]. Increasing the signal to noise ratio is one of pre-processing's key functions in order to improve signal quality. In [12–13] developed a unique Kalman filter-based Bayesian framework and it is able to resolve a significant flaw in model-based filtering, which is the inability to handle signals with various morphologies using a specified model. Nevertheless, applying a Kalman filter is not ideal and actually increase final error levels. In order to enhance the segmentation result, the [14] used a bilateral filter to smooth the image and keep the key borders intact, leaving only the image's overall context. To enhance the protrusion detection performance, it takes the features of human visual perception. Nonetheless, it is necessary to take into account bottom-up saliency detection techniques that enhance performance when combined with pre-processing filters and top-down techniques. Therefore, the Orthogonal Wavelet Filter proposed in this study, which reduces the noise and improves the signal quality. The relevant properties associated with brain activity are then extracted using the feature extraction method. Thus, the Conditional Wasserstein GAN data augmentation strategy is applied to the retrieved features in the manner described by [15–16]. This approach is based on deep generative models and low classification accuracy is caused by features being very congested and lacking a distinct border among features of diverse classes, as evidenced by the distribution of extracted and created features. So, this work utilizes the EMD approach, which records the time-frequency representations of EEG data. For classification of EEG signals several conventional methods such as SVM [17], RNN [18] and CNN [19] are used. However, the problem is the unfair size of class regions, which is lead to inaccurate classification and this issues are resolved by using a developed modified RNN-LSTM classifier. The hyper parameters of the Modified RNN-LSTM classifier is need to be tuned for achieving the better performance. In past various optimization algorithms are used to tune the hyper-parameters of various network and they impose the restrictions on the unsmooth and non-convex nature of the problems [20-21]. To overcome this issues, the proposed work implements the CBO Algorithm, which effectively explores the hyperparameter space and optimizes model performance. The main contributions of this work are

- To reduce undesired interference and preserve relevant emotional information of an EEG signal, an orthogonal wavelet filter is utilized.
- Next, the EMD approach is utilized to obtain the time-frequency representations of the EEG signals.
- A modified RNN-LSTM classifier is used for prediction tasks like categorizing intended movements or orders from EEG signals.
- A CBO Algorithm is used to improve the hyper-parameters of the Modified RNN-LSTM model, hence improving model performance.

II. PROPOSED METHODOLOGY

In recent years, EEG is the most commonly employed because its portability, low cost, easy usage and high temporal resolution. VEP-based BMIs have the potential to help impaired people by offering alternate channels of communication and control due to their information transfer rate is high and minimal need for user training. The proposed work's block diagram is presented in Figure 1.

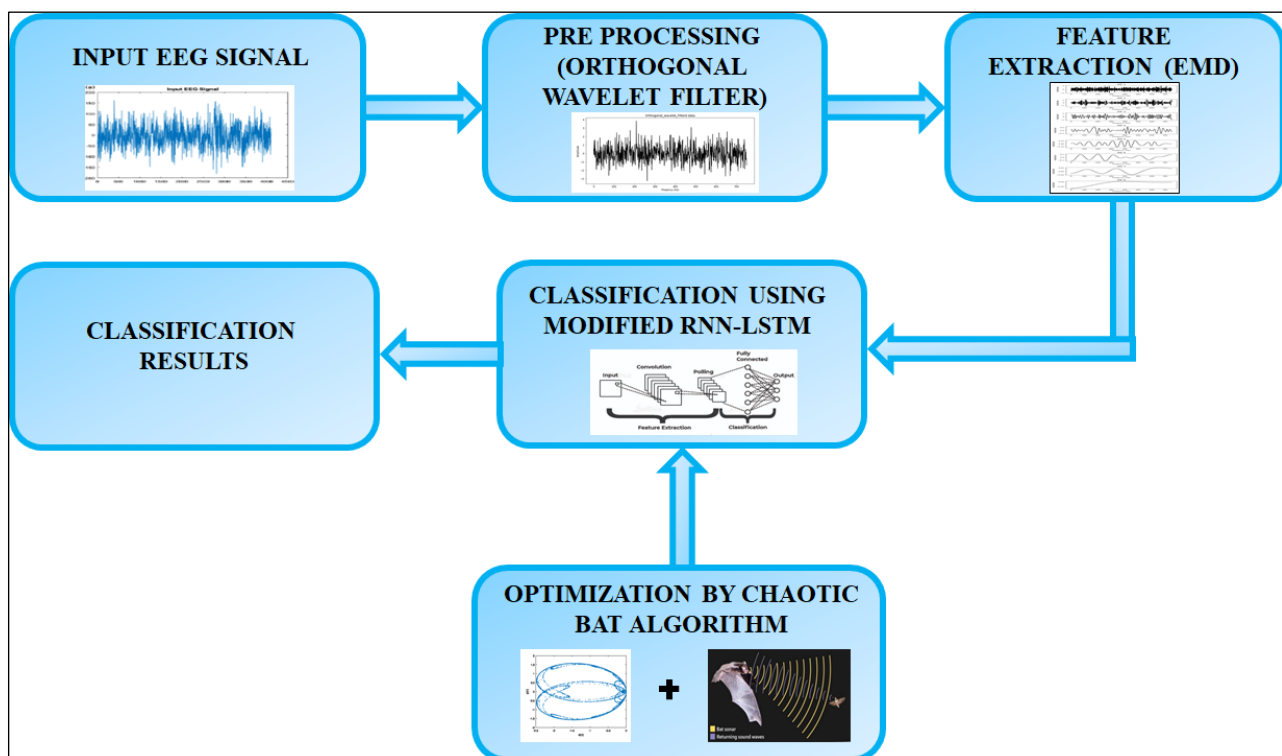


Figure 1: Block Diagram of Proposed Work.
Source: Authors, (2026).

The input signal from EEG are pre-processed by using an Orthogonal Wavelet Filter, which provides excellent flexibility in managing the protection of significant emotional data and the diminution of undesirable interference. This initial pre-processing step ensures that the processed EEG signals are optimally organized for succeeding analysis. Next, to acquire the time-frequency representations of EEG signals, the EMD model is used, which provides a data-driven approach to decay EEG signals into intrinsic mode functions, allowing for the extraction of relevant features related to brain activity. Then it is fed into the modified RNN-LSTM classifier that is used for prediction tasks, such as classifying intended movements or commands from EEG signals. The hyper-parameters of the modified RNN-LSTM model are tuned using a CBO Algorithm, which effectively explores the hyperparameter space and optimizes model performance. Finally, the predicted output is utilized for enhancing the daily functioning of disabled individuals.

II.1 PRE-PROCESSING WITH ORTHOGONAL WAVELET FILTER

Signal improvement and cleaning are the main concerns of pre-processing EEG signals because EEG signals are intrinsically poor, noise from both external and internal sources will easily contaminate them. Human body or electrodes will be the source of the noise and these noises are known as "artifacts." While recording an EEG signal, EEG electrodes able to pick up undesirable electrical physiological signals, such as the Electromyogram from neck muscles and eye blinks. Concerns about motion artifacts resulting from electrode displacement and cable movement also exist when the person moves. Therefore, in order to minimize these artifacts in the raw EEG data, which have an impact on posterior classification, the pre-processing stage is essential. It is important to carefully consider whether these artifacts should be removed because they need to improve the efficacy of emotion detection systems and include important information about emotional states. The bandwidth of the EEG will be reduced by using orthogonal wavelet filters to lessen artifacts in the recorded EEG signals.

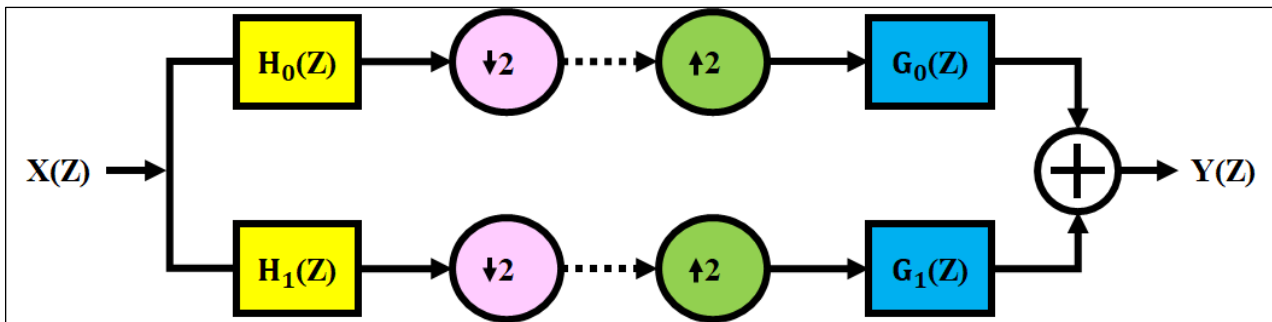


Figure 2: Two-channel orthogonal wavelet filter.

Source: Authors, (2026).

Figure 2 displays the 2 channel wavelet FB. Assume that H_0 and H_1 represent the analysis LPF and HPF in a 2 channel wavelet FB, and that G_1 and G_0 represent the synthesis High pass filter (HPF) and Low pass filter (LPF). Quadrature mirroring will be used to extract the HPFs H_1 and G_1 from LPFs, as shown in Eqn1 and 2.

$$H_1(Z) = Z^{-1}G_0(Z) \quad (1)$$

$$G_1(Z) = ZH_0(-Z) \quad (2)$$

The PR condition in terms of G_0, G_1, H_0 and H_1 is acquired from (3) and c is a constant.

$$H_0(Z)G_0(Z) + H_0(-Z)G_0(-Z) = c \quad (3)$$

In the orthogonal FBs design, LPFs G_0 and H_0 are mirror images that is assumed by Eqn 4.

$$G_0(Z) = H_0(Z^{-1}) \quad (4)$$

The scaling function $\phi(\cdot)$ is expressed as

$$\phi(t) = \sqrt{2} \sum_n h_o[n] \phi(2t - n) \quad (5)$$

In this case, h_o is an LPF that meets the normalization criterion $\sum_n h_o[n] = \sqrt{2}$ and has at least one zero at $z = -1$. In a similar vein, the matching wavelet function $\psi(\cdot)$ is described as,

$$\psi(t) = \sqrt{2} \sum_n h_1[n] \phi(2t - n) \quad (6)$$

In this case, $h_1[n]$ is an HPF that is derived from the LPF using the formula $h_1[n] = (-1)^n h_o[N - 1 - n]$, where N is h_o 's support. Through the usage of the double shifting property on LPF h_o , the orthogonal space covered by the wavelet function ψ and scaling function ϕ is produced. This feature of double shifting will be expressed as

$$\sum_n h_o[n] h_o[n - 2l] = \delta[l] \quad \forall l \in N \quad (7)$$

VMs will be guaranteed by smearing sum rules on $h_o[n]$ coefficients of filter and is defined as

$$H_0^{(K)}(e^{j\pi}) = \sum_n (-1)^n n^k h_o[n] = 0 \quad (8)$$

Where v is the Virtual Machine's (VMs) number; k will be transformed between $0, 1, \dots, v - 1$. From (8), makes clear that v sum rules are necessary for v VMs and there is no dc leakage when the value of $v \geq 1$ (which indicates that there are multiple VMs). It is expressed as

$$H_o(e^{j\pi}) = H_1(e^{j0}) = 0 \quad \text{for } v \geq 1 \quad (9)$$

Thus, it confirms that there is a zero dc leakage and after pre-processing the signal undergoes with feature extraction for extracting the feature by using EMD method.

II.2 FEATURE EXTRACTION USING EMD

The primary objective of feature extraction in the EEG-based emotion detection method is to extract data that accurately captures an emotional state of an individual. The extracted features are mostly responsible for determining the emotion identification's accuracy. Next, it is vital to isolate key EEG characteristics associated with states of emotion. EEG feature analysis using time-frequency domains for emotion recognition will be covered in this part.

II.2.1 Time-Frequency Domain Analyses

The time-frequency domain analysis technique, which incorporates data from the time and frequency domains. Time-varying and non-stationary signals are captured effectively by time-frequency-domain characteristics, then it is utilized to characterize different emotional states. Next, the EMD approach is utilized to obtain the time-frequency representations of the EEG signals. For the study of nonlinear and non-stationary data, EMD is a data-driven decomposition technique that decay the signal into a finite number of smaller IMFs, making it possible to extract pertinent aspects associated with brain activity. A sum of IMFs will be used to describe a non-stationary signal, and each IMF should adhere to the following two necessities:

- 1) The IMFs' numbers of extrema and zero crossings should be equivalent, or deviate by no more than one.
- 2) Two envelopes defined by local maxima and minima should have a mean value of zero.

IMFs will be retrieved from a signal using the shifting process, an iterative technique that works as follows:

Connect the detected maxima and minima separately from the signal $x(t)$ to create the upper (e_{max}) and lower (e_{min}) envelopes using the cubic spline interpolation method. Compute the mean by

$$m(t) = \frac{e_{max} + e_{min}}{2} \quad (10)$$

Extract the difference $d(t)$ among signal $x(t)$ and calculated $m(t)$

$$d(t) = x(t) - m(t) \quad (11)$$

Check whether $d(t)$ is fulfilling the IMFs simple conditions. Repeat stage 1 to 3 until $d(t)$ fulfilling the IMFs conditions. If $d(t)$ fulfils IMFs condition once, define the initial IMF as $IMF_1 = d(t)$. By producing residue $r(t)$ as $r(t) = x(t) - IMF_1$, one will collect the subsequent IMFs and utilize these residues as the initial data for the subsequent iteration. When the final residue is either a constant or monotonic function, or a function that is incapable of producing any more IMFs, the iteration will come to an end. The real signal will be denoted as the summation of all IMFs and last residual.

$$x(t) = \sum_{i=1}^K IMF_i + r_K(t) \quad (12)$$

Where $r_K(t)$ is the final residual, K is the IMF number, and IMF_i is the i^{th} IMF. After feature extraction, a modified RNN-LSTM classifier is used for prediction tasks, like categorizing planned movements or commands from EEG signals.

II.3 A MODIFIED RNN-LSTM FOR CLASSIFICATION

Modified RNN is employed for classification after feature selection to detect the class label. The normal feed-forward neural network is extended upon by an artificial neural network type called RNN. An RNN is able to process successive inputs, each of which reflects the firing of the phase before it at each step. One particular type of RNN that will learn from lengthy dependence is called an LSTM. An example of a long-term reliance on a recurrent hidden unit is long awful memory. A typical recurrent layer computes a weighted linear average of the inputs prior to applying a nonlinear function. A recurrent layer with LSTM also forms a memory cell.

For a hyper spectral picture classification task, supply a hyper spectral pixel sequence $x = (x^1, x^2, \dots, x^k)$ to the input layer. A recurrent layer based on LSTM C_t creates a memory cell at step t . Compute the activation of processing layers by

$$h_t = o_t \tanh(c_t) \quad (13)$$

Here, the output gate that chooses which section of the memory material to display is represented by $o_t \tanh(\cdot)$, which is also the hyperbolic tangent function. Modify the output layer using the following formula.

$$o_t = \sigma(W_{oix_t} + W_{oh}h_{t-1} + W_{occ_T}) \quad (14)$$

Weight matrices or W , are used here. The input-output weight matrix is called W_{oi} , and the memory-output weight matrix is denoted by W_{oc} . Logistic sigmoid function $\sigma(\bullet)$ is used. New memory cell (C_t) content is inserted, and some of the current memory material is deleted, to modify memory cell C_t .

$$C_t = i_t \odot \bar{C}_t + f_t \otimes C_{t-1} \quad (15)$$

Where $\odot$ denotes element wise multiplication and the new memory cell content C_t is calculated by

$$\bar{C}_t = \tanh(W_{cix_t} + W_{ch}h_{t-1}) \quad (16)$$

Then the hyper parameters of the modified RNN-LSTM model are tuned using a Chaotic Bat Algorithm, which effectively explores the hyperparameter space and optimizes model performance.

II.4 MODIFIED RNN-LSTM PARAMETER OPTIMIZATION USING CHAOTIC BAT ALGORITHM

A Chaotic Bat Algorithm is used to tune the hyper parameters of the modified RNN-LSTM model. This method efficiently explores the hyperparameter space and maximizes model performance.

II.4.1 The basic bat algorithm

A Bat Algorithm (BA) was motivated by the echolocation behavior of bats. The size of bats in the wild varies greatly; they surely weigh as little as 1.5 g or as much as 1 kg. Bats utilize a mechanism called echolocation to find and navigate to their prey. Bats detect distance using frequency modulated signals, which have pulses that last between 8 and 10 ms and fall between 25 and 100 KHz in frequency. Bats typically release 10–20 of these bursts every second. However, produce brief bursts of over 200 pulses per second when hunting. Loudness is another feature of these pulses; when hunting or seeking prey, bats will produce ultrasonic pulses that are up to 110 dB loud. However, these pulses become weaker as they get closer to the target. The frequency of every bat is

$$f^i = f^{min} + r_1(f^{max} - f^{min}) \quad (17)$$

The frequencies that are permitted are denoted by f^{min} and f^{max} and the frequency for i th bat is represented by f^i . In this case, r_1 is a random number with uniformly distribution within the interval $[0, 1]$.

II.4.1.1 Exploration or diversification

The velocity V^i and position X^i are updated by

$$V^i(t+1) = V^i(t) + f^i(X^i(t) - X^{best}(t)) \quad (18)$$

$$X^i(t+1) = X^i(t) + V^i(t+1) \quad (19)$$

The position with the highest fitness in the current population is denoted by X^{best} , where t is the current iteration number. It is expected that V^i is 0 at startup.

II.4.1.2 Exploitation Or Intensification

With a random walk, local search or exploitation is conducted. For each bat in the population, two parameters are updated at each iteration: the loudness $A^i(t)$ and the pulse emission rate $R^i(t)$. A local search is carried out, either around the optimal solution or a randomly selected solution, depending on $R^i(t)$:

$$X^{i,new}(t) = \begin{cases} X^{best}(t) + r_3 A^i(t) & \text{if } r_2 > R^i(t) \\ X^r(t) + r_3 A^i(t) & \text{else} \end{cases} \quad (20)$$

Where $r[1,2, \dots, N_b]$, $r \neq i$ is a randomly selected integer, and $r_2 [0,1]$ and $r_3 [-1,1]$ are uniformly distributed random numbers. Stated differently, $X^r(t)$ represents a solution that was selected at random in the current iteration and is distinct from the i th solution. A competition-style selection process centered on fitness, where the old solutions compete against the new ones. With a probability $A^i(t)$, the more fit answer takes the place of the less fit one.

$$X^i(t) = X^{i,new}(t), \text{ if } f(X^{i,new}(t)) < f(X^i(t)) \text{ and } r_4 < A^i(t) \forall i, i[1,2, \dots, N_b] \quad (21)$$

In this case, the random number $r_4 [0,1]$ has a uniform distribution. Lastly, while the iterations go on, each bat's loudness (A^i) and pulse emission rate (R^i) are updated:

$$A^i(t+1) = \alpha A^i(t) \quad (22)$$

$$R^i(t+1) = R^i(0)[1 - \exp(-\gamma t)] \quad (23)$$

Here, $A^i(0)[1,2]$, $R^i(0)[0,1]$ both randomly generated within their respective limits.

II.4.2 Chaotic Bat Optimization (Cbo) Algorithm

The most significant flaws in the classical BA are seen in the experimental results of the classical BA over benchmark functions: premature and/or erroneous convergence. The primary cause of this is the parameters' random initialization.

The sequences generated during the random initialization procedure are not evenly dispersed, which causes varying outcomes in various runs. The initialization procedure must be carried out in a way that ensures initial sequences are evenly dispersed in order to address these issues. If the numbers in a chaotic sequence are far from the unusual attractors of the chaotic map, they are well dispersed. Strange attractors in chaotic maps occur in a unique parameter space; however, in this approach, parameters are specified in a way that eliminates them, avoiding attractor-related issues.

Therefore, utilizing chaotic sequences will be a very effective strategy to produce well-distributed sequences for handling the algorithm's premature and incorrect convergence. Figure 3 displays the CBA flowchart. Chaotic sequences are utilized to establish frequencies, loudness, and pulse emission rates in order to enhance the performance of the conventional BA. An important component that influences the trade-off between algorithmic exploration and exploitation is the loudness of AI. Since " α " is smaller than unity, this is monotonically decreased in the basic BA as the iterations go on. Better outcomes, however, have been documented when a chaotic map or sequence is used to vary the volume of AI.

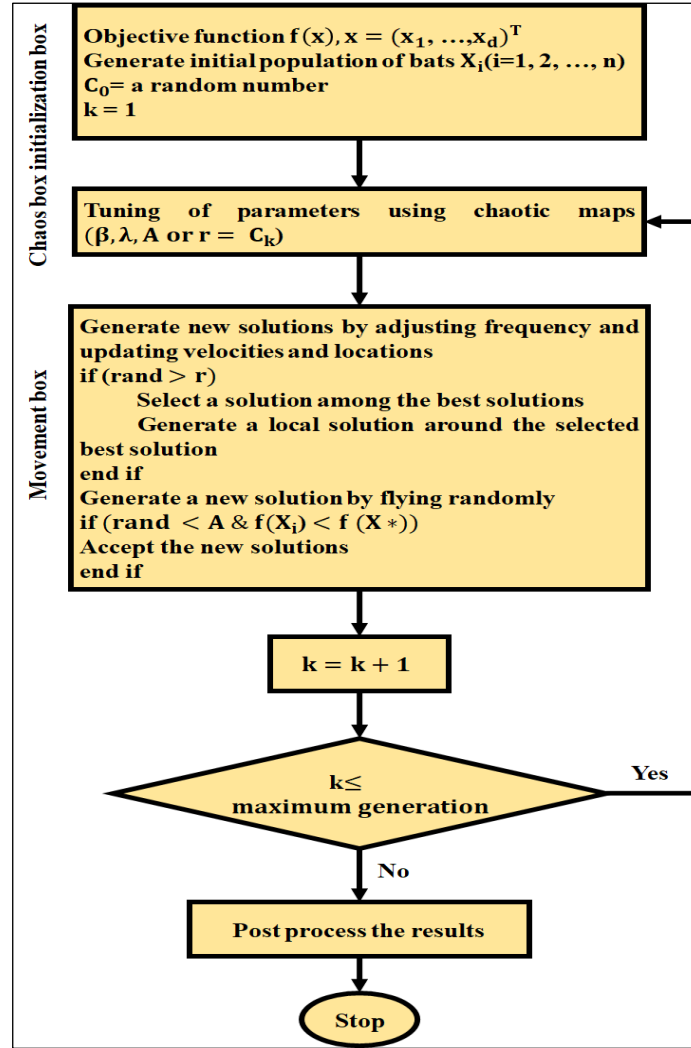


Figure 3: Flowchart of CBO.

Source: Authors, (2026).

In order to train AI to optimize three unimodal and three multimodal functions, several chaotic sequences were tested. The sinusoidal map (or sequence) yielded the best results. Using the sinusoidal map, the variation of the loudness A^i is provided by

$$A^i(t+1) = a\{A^i(t)\}^2 \sin(\pi A^i(t)) \quad (24)$$

Here, $A^i(0)[0,1]$ is randomly generated.

III. RESULTS AND DISCUSSION

A comprehensive approach is proposed to improve the performance of VEP-based BMIs through the integration of advanced signal processing techniques and explainable AI methods. During the pre-processing phase, an orthogonal wavelet filter is used, which provides remarkable flexibility in managing the retention of pertinent emotional information and the elimination of undesired interference. With the use of EMD's data-driven methodology, pertinent features pertaining to brain activity will be extracted. A modified RNN-LSTM classifier is used for prediction tasks and a Chaotic Bat Algorithm is used to tune the hyper-parameters of the modified RNN-LSTM model. This method efficiently explores the hyperparameter space and maximizes model performance. Overall it is implemented in python software and comparative analysis is done with other methods to show the better performance of the work.

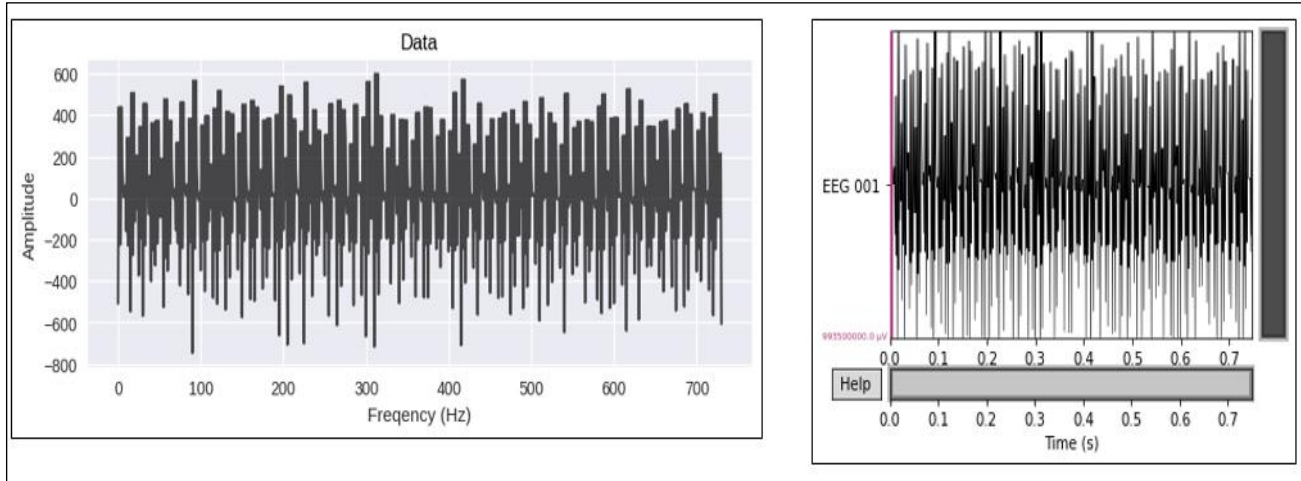


Figure 4: Input EEG signal.
Source: Authors, (2026).

Figure 4 shows the input signal of EEG from EEG dataset and it is used for the classification process. EEG signal is achieved by amplifying and recording the spontaneous biological potential of the brain on the scalp.

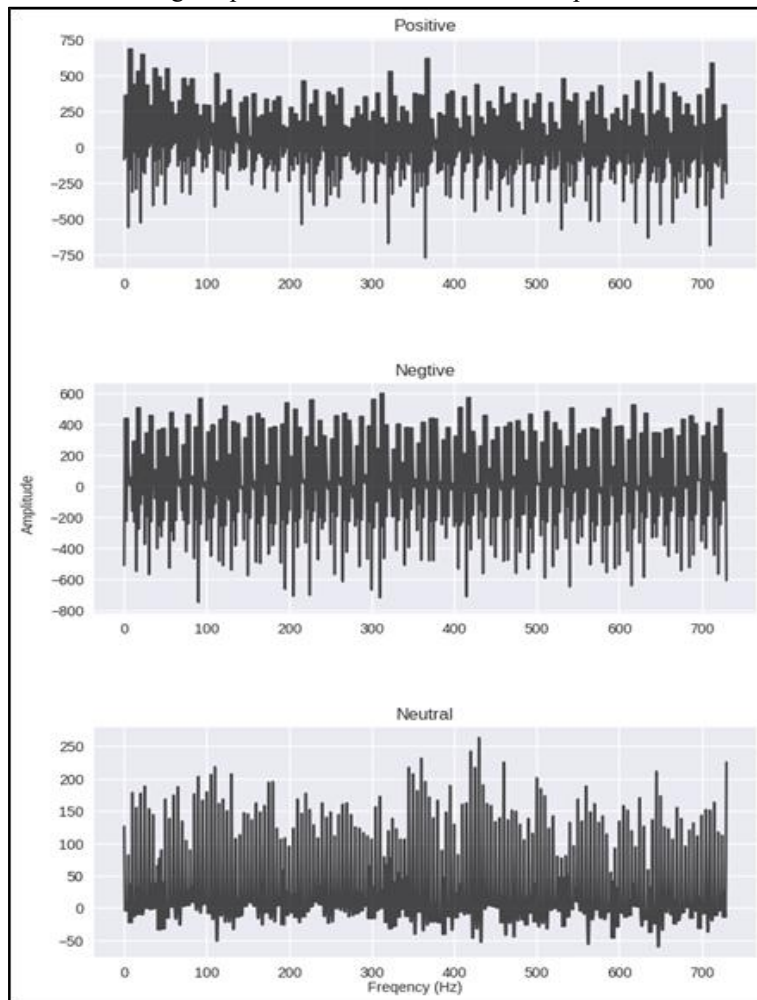


Figure 5: Positive, negative and neutral waveform of input EEG signal.
Source: Authors, (2026).

Figure 5 shows the positive, negative and neutral waveform of input EEG signal. The outcomes of positive EEG signal values are in descending waves and negative values are in ascending waves.

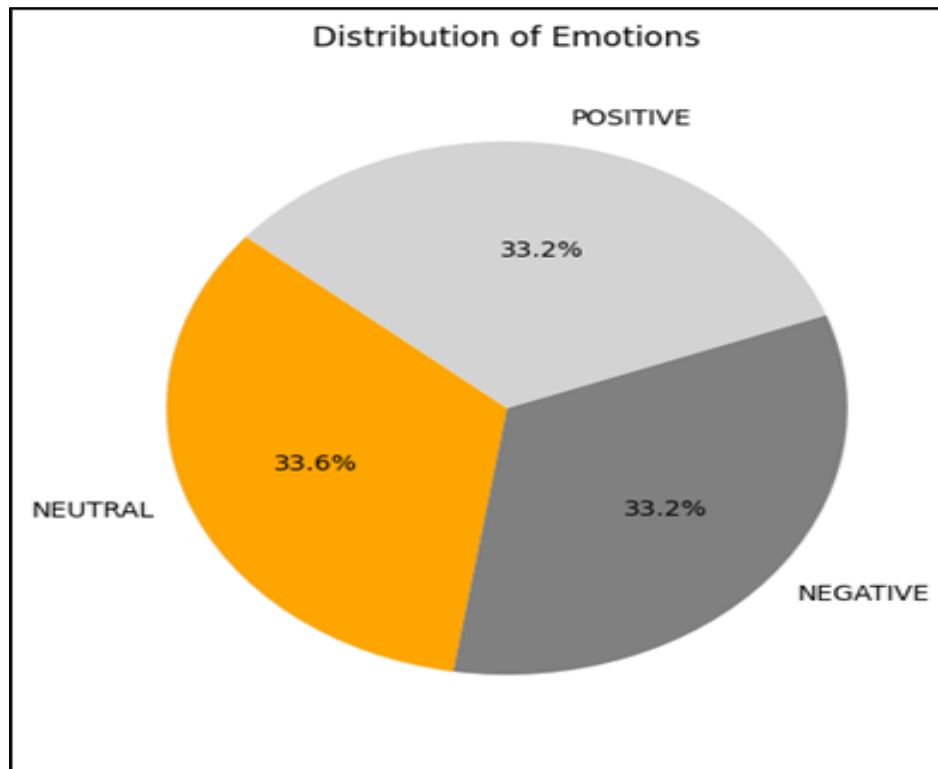


Figure 6: Distribution of Emotions.
Source: Authors, (2026).

Figure 6 displays the distribution of emotions with positive, neutral and negative aspects. The positive and negative emotions are 33.2%, the neutral emotions are 33.6 %.

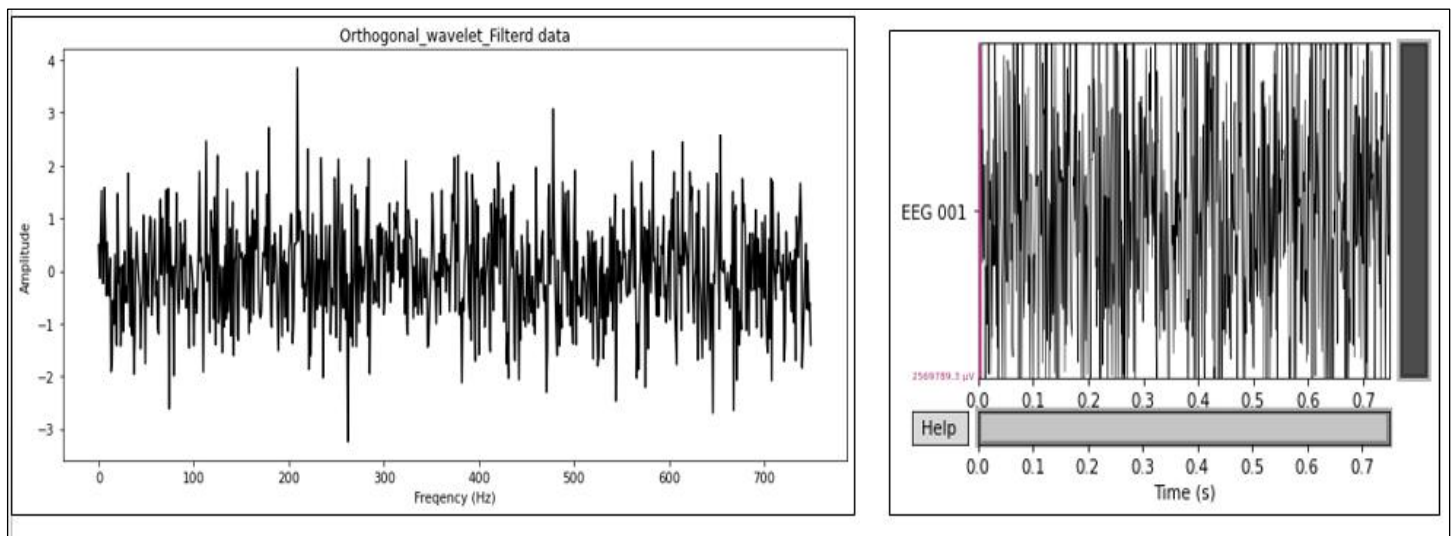


Figure 7: Filtered Data with Orthogonal wavelet filter.
Source: Authors, (2026).

Figure 7 represents the filtered data with orthogonal wavelet filter. The input signal is pre-processed by using an orthogonal wavelet filter. It removes the unwanted noise and interference from the input signal.

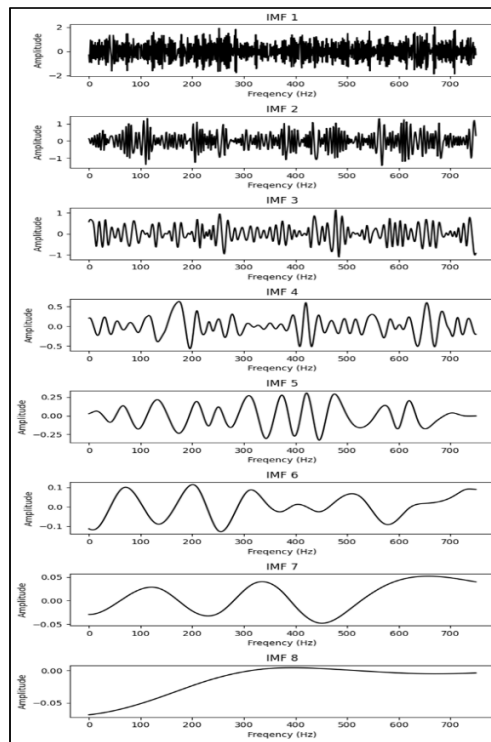


Figure 8: Feature extraction using EMD approach.
Source: Authors, (2026).

Figure 8 shows the Feature extraction using EMD approach. It is utilized to acquire the time frequency representation of the EEG signal. EMD provides a data-driven approach to decay EEG signals into IMFs, allowing for the extraction of relevant features related to brain activity.

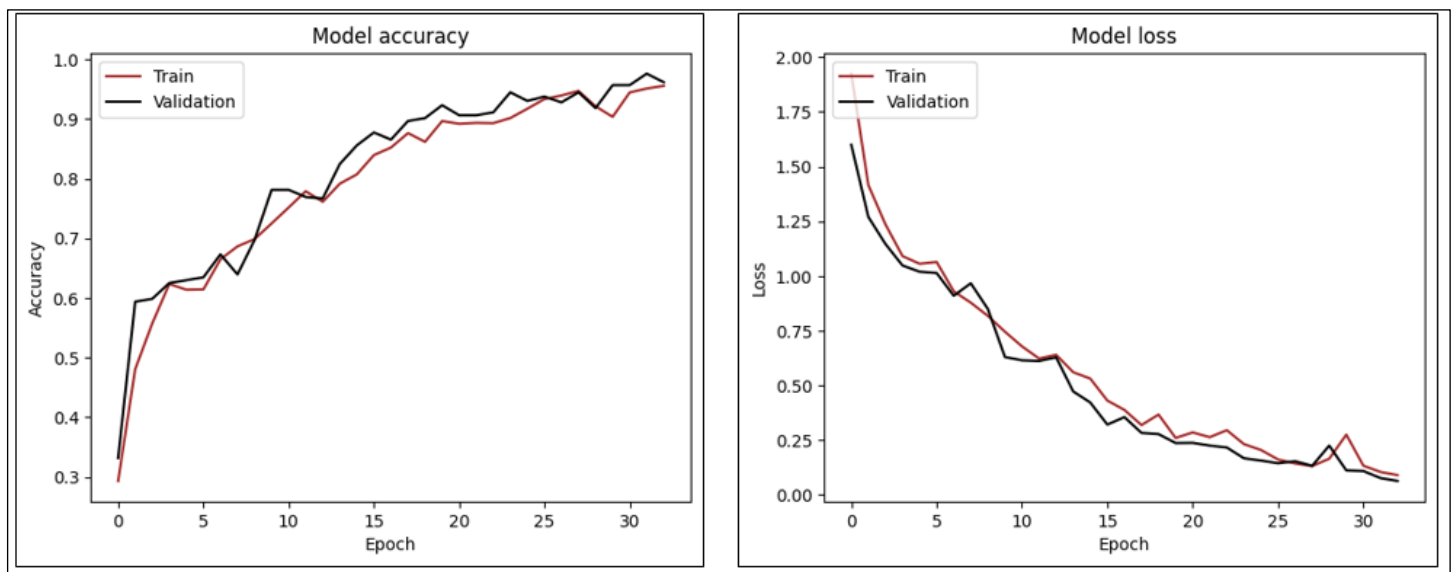


Figure 9: Training and validation results.
Source: Authors, (2026).

Figure 9 indicates the training and validation results. The RNN-LSTM classifier achieves an accuracy of 96% with small amount of loss. Figure 10 displays the confusion matrix of the Modified RNN-LSTM classifier. Each row and column in the confusion matrix denotes the target and the projected class.

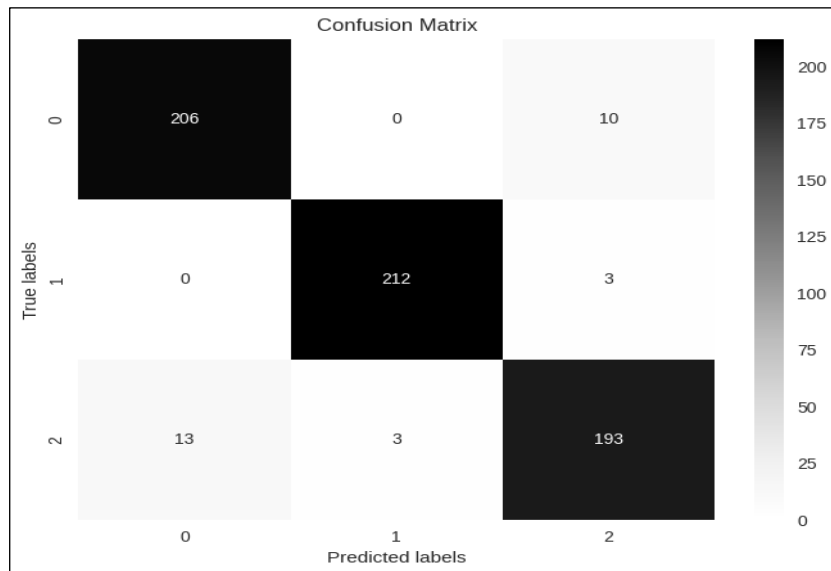


Figure 10: Confusion matrix.

Source: Authors, (2026).

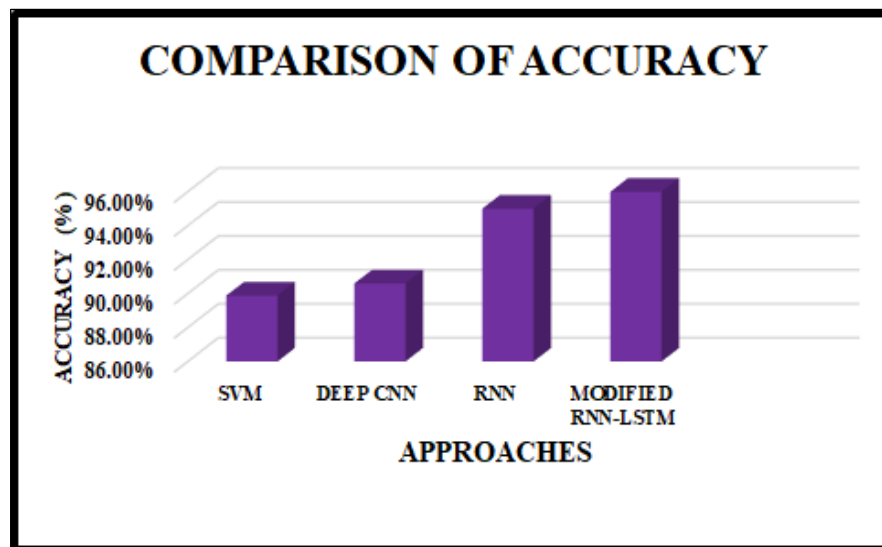


Figure 11: Comparison of Accuracy.

Source: Authors, (2026).

Figure 11 depicts the accuracy comparison for various methods like SVM, Deep CNN, RNN and modified RNN-LSTM. The modified RNN-LSTM attained a highest accuracy of 96 % which is better than SVM [22], Deep CNN [23] and RNN [24] methods.

Table 1: Classification measures for each positive, neutral and negative state of emotion.

Dimensions	Accuracy (%)	Precision (%)	F1-score (%)
Positive	87.96	78	81
Neutral	82.41	72	73
Negative [25]	79.63	75	71
Positive	98.23	94.012	93.68
Neutral	97.95	92.89	93.32
Negative [26]	94.54	92.087	92.65
Positive	98.45	94.45	94.46
Neutral	98	93.12	93.78
Negative [Proposed work]	95	93.06	93.05

Table 1 highlights the classification measures for each positive, neutral and negative emotional State. The proposed method attains the accuracy, precision and F1-score with positive, neutral and negative emotion states are 98.45%, 93.12 % and 93.05 %.

Source: Authors, (2026).

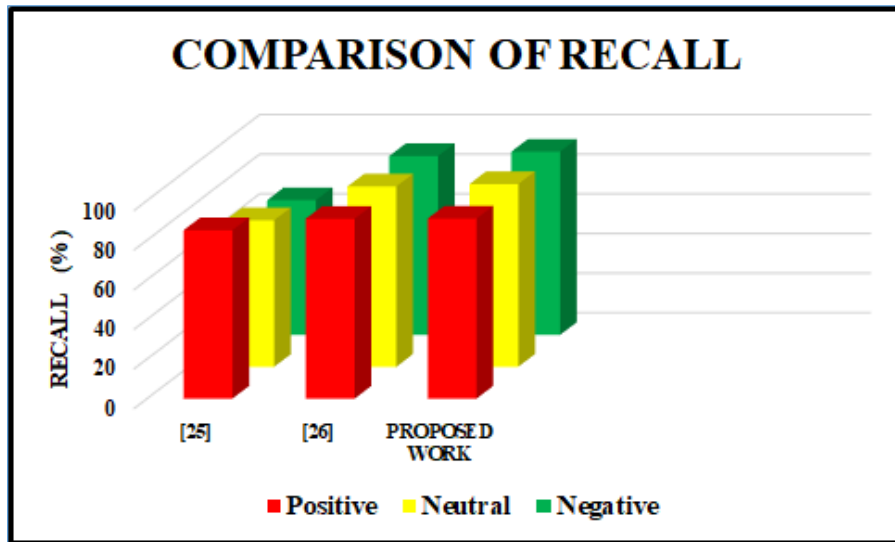


Figure 12: Comparison of Recall.
Source: Authors, (2026).

Figure 12 depicts the recall comparison with positive, neutral and negative emotional state. From the comparison, the proposed model attained a recall value of 90.89%, 92.24% and 92.47 % for positive, neutral and negative emotional state.

III. CONCLUSIONS

This paper proposes a novel method to boost the performance of VEP-based BMIs through the integration of advanced signal processing techniques and explainable AI methods. An orthogonal wavelet filter is initially employed to pre-process EEG signals by reducing undesired interference. The EMD method is then applied to obtain the time-frequency representations of the EEG data, which enables the extraction of pertinent features associated with brain activity. A modified RNN-LSTM classifier is used for prediction tasks and A Chaotic Bat Algorithm is used to tune the hyper-parameters of the modified RNN-LSTM model. This method efficiently explores the hyperparameter space and maximizes model performance. The method is evaluated by using python software and comparative analysis is done with other methods. Performance metrics including classification accuracy, recall precision and F1 score are utilized to measure the efficacy of the proposed methodology. As a result, the modified RNN-LSTM model achieves a highest accuracy of 96 % and better performance interms of Recall, Precision and F1-score.

IV. AUTHOR'S CONTRIBUTION

Conceptualization: Kalakonda Jyothsna, Ravichander Janapati, Viswaprakash Babu
Methodology: Kalakonda Jyothsna, Ravichander Janapati, Viswaprakash Babu
Investigation: Kalakonda Jyothsna, Ravichander Janapati, Viswaprakash Babu
Discussion of results: Kalakonda Jyothsna, Ravichander Janapati, Viswaprakash Babu
Writing – Original Draft: Kalakonda Jyothsna, Ravichander Janapati, Viswaprakash Babu
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Resources: Kalakonda Jyothsna, Ravichander Janapati, Viswaprakash Babu
Supervision: Kalakonda Jyothsna, Ravichander Janapati, Viswaprakash Babu
Approval of the final text: Kalakonda Jyothsna, Ravichander Janapati, Viswaprakash Babu

V. REFERENCES

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