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Deep Learning-Based Brain-Computer Interface for Accurate EEG Signal Decoding

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***Abstract*—One of the most cutting-edge technologies available today, brain-computer interface (BCI) systems rely heavily on the interpretation of electroencephalogram (EEG) data to allow for real communication between the human brain and an external device. This research presents a deep learning-based EEG categorization algorithm that might enhance BCI accuracy and real-time performance. The work utilizes the BCI Competition IV 2a dataset and focuses on enhancing the decoding of motor imagery EEG signals using sophisticated machine learning and deep learning architectures including TCFormer Fusion, SNN, ATCNet, CNN, and RNN. Ensuring sufficient representation of temporal and spatial interdependence, the proposed system incorporates preprocessing, feature extraction, and classification of EEG signals. In comparison to the other models, the RNN model outperforms them all with impressively high values for accuracy (ACC)—94.7%—precision (PRE)—recall (REC)—and F1-score (F1)—94.8%. The results demonstrate the efficacy of RNNs for learning sequential EEG patterns. In summary, the proposed method offers substantial enhancements in EEG signal decoding ACC, showcasing its potential suitability for dependable and effective BCI systems in healthcare and assistive technology.**

Keywords—Brain–Computer Interface, Human–Machine Intelligence, Deep Learning, Continuous Pursuit, Motor Imagery, Electroencephalogram, EEG Channel Selection.

I. INTRODUCTION

The evolution of healthcare requires intelligent technologies to restore motor and communication functions, leading to better independence, rehabilitation and quality-of-life outcomes for patients [1][2]. The Brain-Computer Interface (BCI) brings together disciplines such as electronics, computer science, psychology, neurology, pattern recognition, and signal processing to understand and translate brain impulses into orders for action [3]. These signals are based on neural signals that are measured from the brain to determine what a user wants to use their motor or cognitive abilities to accomplish, which in turn can be used to restore or improve the quality of life. Brain computer interfaces (BCI) are systems that convert brain activity into signals or commands that are then used to control external equipment like prostheses, communication devices, neurorehabilitation devices, and assistive technology for everyday tasks [4][5].

In medical applications, BCI systems are particularly crucial, as they offer an alternate means of communication for those with serious neurological disabilities [6][7][8][9]. Patients suffering from neurological disorders, brain tumours, spinal cord injuries, traumatic brain injuries, or stroke may have significant difficulties with motor control and communication. Motor control and speech function can be severely affected in patients with neurological disorders, brain tumours, spinal cord injuries, traumatic brain injuries, and strokes. In these situations, patients might not be able to communicate or move voluntarily, which can have a profound impact on their independence [10]. BCIs do not rely on the integrity of damaged neuromuscular pathways, and allow direct brain-to-device communication, thus offering a possible avenue for communication and functional control restoration in damaged individuals [11][12]

BCI systems can get brain signals in two ways: invasively and non-invasively. There are intrusive methods that provide high-quality signals, such as inserting electrodes directly into the brain. However, these methods require invasive surgery and come with some health hazards [13][14][15]. These are all non-invasive techniques, including electroencephalography (EEG), which is used to measure brain activity from the outside of the scalp. However, given their increased susceptibility to noise and lesser spatial resolution, EEG signals are frequently utilised in large-scale applications because of their practicality, low cost, portability, and safety. Most commonly used non-invasive methods for real-time signal decoding and assistive usage are BCI systems based on EEGs [16][17][18].

Recent developments in the field have centered on the use of ML and DL algorithms to enhance the capabilities of EEG-BCI systems, allowing for the decoding of intricate brain signals with greater ACC. EEG signals are analyzed for meaningful patterns and these patterns are classified into known mental or motor states [19] and then converted into control commands to be used for external devices [20][21]. DL frameworks, especially, improve the ACC of feature learning and classification of brain signals by learning nonlinear relationships. Moreover, optimization methods like probabilistic hyperparameter modelling can enhance the efficiency and performance of the model, achieving better results than classic ML methods in EEG signal decoding while maintaining an exploration-exploitation balance in parameter tuning [22][23].

A. *Motivation and Contribution*

The motivation of this study is to increase the ACC and reliability of EEG signal decoding in BCI systems, which is difficult because brain signals are noisy, nonlinear and complex. Current strategies are not able to successfully record the long-term temporal association in motor imagery EEG data, yielding poor classification results. Decoding ACC may be improved by exploring sophisticated DL models like RNN, which can successfully learn sequential patterns. Facilitating efficient real-time BCI applications in healthcare and assistive technology is the goal of this effort. This research offers several key contributions as listed below:

- Proposed an advanced EEG signal decoding framework for BCI applications using DL techniques.
- Evaluated multiple ML and DL models including TCFormer Fusion, SNN, ATCNet, CNN, and RNN for comparative performance analysis.
- Developed a robust preprocessing pipeline involving artifact removal, filtering, normalization, and data augmentation to enhance EEG signal quality.
- A RNN-based model is proposed for EEG signal decoding in Brain-Computer Interface (BCI) applications.
- Extracted meaningful temporal and spatial EEG features to improve classification ACC of motor imagery tasks.
- Highlighted the effectiveness of recurrent architectures in capturing sequential dependencies in EEG signals.
- Provided an improved and reliable approach for accurate EEG-based BCI systems suitable for real-time applications.

The justification of the proposed work lies in the complexity of EEG signals, which are nonlinear, non-stationary, and highly noisy, making accurate decoding difficult for BCI systems. Traditional models fail to effectively capture long-term temporal dependencies present in motor imagery EEG data. The novelty of this study is the use of an RNN-based framework that efficiently learns sequential patterns and temporal dynamics from EEG signals. Additionally, the proposed approach integrates a complete pipeline of preprocessing, feature extraction, and deep sequential learning to improve classification performance and reliability.

B. *Organization of the Paper*

The structure of the paper is as follows: Section II presents a review of related work on accurate EEG signal decoding using brain-computer interfaces, Section III describes the dataset, preprocessing steps, and model implementation, Section IV discusses the experimental results along with comparative analysis, and Section V concludes the study by summarizing the key findings and outlining directions for future research.

II. LITERATURE REVIEW

This section reviews recent studies on motor imagery EEG decoding, highlighting advances in DL, feature extraction, attention mechanisms, graph-based models, and hybrid classification techniques that have improved decoding ACC, computational efficiency, and the practical performance of brain–computer interface systems.

Chen et al. (2026) To address these challenges, a novel deep neural network, MPSTANet (Multiscale Pooling Spatial–Temporal Attention Network), is proposed for accurate MI decoding with both small-sample and large-scale datasets. MPSTANet integrates mix pooling with spatial–temporal attention to effectively extract and preserve spatial–temporal EEG features. The feature calibration process begins with local and global spatial attention, multiscale temporal attention, mix pooling, feature fusion, and channel interaction attention (CIA). Then, 3-D weight attention (3-DWA) is used. Experiments on four public datasets demonstrated superior performance in both small-sample and subject-independent scenarios, highlighting the robustness and potential of MPSTANet for BCI applications[24].

Narayan et al. (2026) suggests an EEG categorisation model that uses DL to enhance the PRE and functionality of BCI devices in real-time. The model is based on a combination of CNNs for extracting spatial features and LSTM networks for learning temporal patterns; it also makes use of band-pass filtering and ICA. With a latency of only 245 milliseconds and an ACC of 92.4%, the suggested CNN-LSTM model blew away the competition, according to the experimental data [25].

V et al. (2025) uses the BCI Competition IV Dataset 2b to train a DC-GCN for EEG classification using the Chaotic Sea-Horse Optimiser (CSHO). Prior to feature extraction using Fast Fourier Transform (FFT), EEG data undergo preprocessing using bandpass filtering and Common Average Referencing. Outperforming 1D-CNN, RNN, LSTM, DBN, SVM, and ELM, the suggested technique attained an average ACC of 92.47%, F1 of 92.53%, REC of 93.29%, and PRE of 91.29% [26].

Yang et al. (2024) suggests using ensemble learning, feature fusion, and feature-dependent frequency band selection to create DSFE, a new EEG decoding framework for finger motor imagery. The method uses correlation coefficient-based frequency band selection (FDCC), feature fusion, and a weighted voting ensemble to improve decoding performance. Experiments on a public five-finger motor imagery dataset achieved the highest decoding ACC of 50.64%, outperforming existing methods by 7.64%[27].

Doudou, Reffad and Mebarkia (2023) introduces DWT-based features to improve MI-EEG signal decoding. The BCI Competition II Dataset III was used to extract and analyse 18 features from the time and frequency domains using SVM, LR, KNN, and LDA classifiers. The LR classifier achieved the best performance with 92.14% classification ACC, which was maintained using only six genetically optimized features, demonstrating the effectiveness of the proposed approach[28].

Yan, Xu and Li (2023) offers a MDR system that has three layers: an interaction executive layer, a layer that decodes intentions, and a layer that evokes MI-EEG. The proposed TSFF-LightGBM network combines temporal–spectral feature fusion with LightGBM to improve decoding ACC

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while reducing decoding time. Integrated with VR, a multi-DOF wearable robot, and synchronized visual and kinesthetic feedback, the system enhances human–machine interaction. Experimental results achieved average accuracies of 75.89% on the BCI IV 2a dataset and 93.53% on the HGD dataset, demonstrating its effectiveness for practical BCI rehabilitation applications[29].

Table I summarizes recent studies on EEG signal decoding, highlighting proposed methodologies, datasets, key performance outcomes, and identified research limitations and future directions.

TABLE I. RECENT STUDIES ON ACCURATE EEG SIGNAL DECODING USING A BRAIN-COMPUTER INTERFACE

Author	Proposed Work	Dataset	Findings	Limitations & Future Work
Chen et al. (2026)	Proposed MPSTANet integrating multiscale pooling and spatial–temporal attention for MI decoding.	BCI Competition IV 2a, OpenBMI, BCI Competition IV 2b, PhysioNet	Superior cross-session performance across four public datasets.	High computational complexity; further optimization is needed for real-time and resource-constrained BCI systems.
Narayan et al. (2026)	Developed a CNN–LSTM model with band-pass filtering and ICA for EEG classification.	Public MI-EEG dataset	Achieved 92.4% accuracy with 245 ms latency.	Limited evaluation on cross-subject and cross-session scenarios; robustness should be further validated.
V et al. (2025)	Introduced DC-GCN + CSHO for EEG classification using graph learning and evolutionary optimization.	BCI Competition IV Dataset 2b	Achieved 92.47% accuracy, outperforming several baseline models.	Computational overhead may limit deployment in real-time embedded BCI applications.
Yang et al. (2024)	Proposed DSFE combining feature-dependent frequency band selection, feature fusion, and ensemble learning.	Public Five-Finger Motor Imagery Dataset	Achieved 50.64% decoding accuracy, improving previous methods by 7.64%.	Performance remains relatively low for practical multi-class BCI systems; further enhancement is required.
Doudou et al. (2023)	Introduced DWT-based feature extraction with optimized feature selection for MI-EEG classification.	BCI Competition II Dataset III	92.14% classification accuracy using LR with six optimized features.	Relies on handcrafted features; integration with deep learning could improve feature representation.
Yan et al. (2023)	Developed an MDR system using TSFF-LightGBM, VR, and wearable robotic feedback for MI rehabilitation.	BCI IV 2a, HGD	Achieved 75.89% and 93.53% average accuracies on the two datasets.	Primarily focused on rehabilitation; broader validation across diverse BCI tasks and subjects is still needed.

Research gaps: DL and hybrid models have made great strides in EEG-based BCI systems, but there are still many unanswered questions about how to decode complicated brain signals. Existing methods are limited in their ability to adequately model long-term temporal and spatiotemporal dependencies of noisy EEG signals. Further, some models do not perform well on a variety of subjects and datasets, which reduces their applicability to the real world. Additionally, real-time BCI applications necessitate designs that are both computationally efficient and lightweight.

III. RESEARCH METHODOLOGY

The suggested technique makes use of the EEG dataset from the BCI Competition IV 2a, which has nine individuals doing motor imagery tasks at 250 Hz with 22 channels utilising the 10-20 system. Artefact removal, bandpass filtering, denosing, Z-scoring, and data segmentation into 2-second intervals with overlapping windows for data augmentation are all part of the preprocessing steps for the EEG data. In order to assess the classification performance of a DNN, Train it on the features that have been extracted and then use metrics like REC, ACC, PRE, and F1. Figure 1 shows the suggested flow diagram for ML-based brain-computer interface EEG signal decoding. In the section that follows, layout the recommended technique step by step:

A. Data Gathering and Analysis

The BCI Competition IV 2a dataset, which contains EEG signals captured from nine subjects as they imagined various motor actions, is used in this work. This EEG data was collected with 22 electrodes at a 250 Hz sampling rate following the International 10-20 technique. The following are examples of data visualizations that were employed to analyses the distribution of attacks, feature correlations, etc.: bar plots and heatmaps:

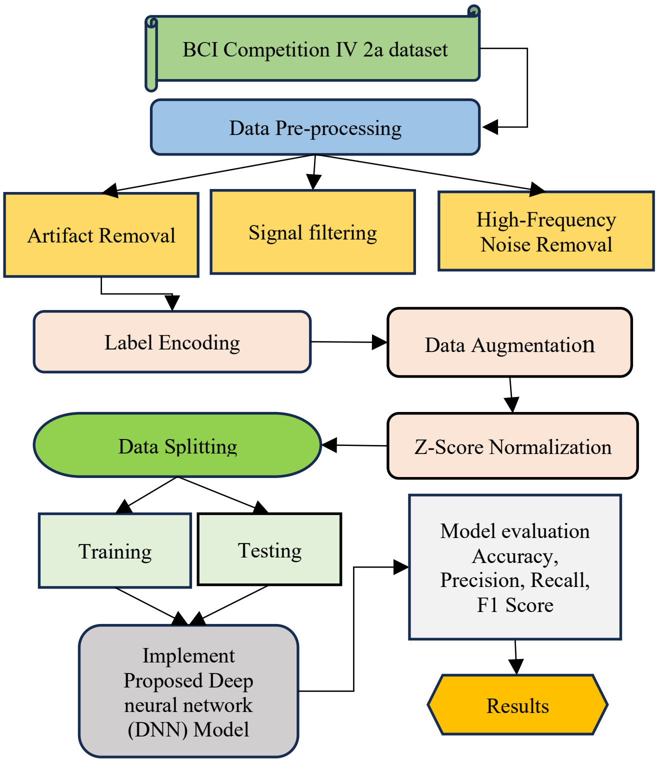

Fig. 1. Proposed flowchart for accurate EEG signal decoding using a brain-computer interface using machine learning

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Figure 2 shows a PSD comparison of the unfiltered EEG signal (blue) with the filtered signal (red). The highlighted green area (8–30 Hz) indicates the frequency range of interest which shows that in this frequency range, the filtered signal retains the essential components of the EEG signal and rejects noise components at low and high frequencies. The improved EEG signal quality for precise feature extraction and BCI analysis is a direct result of the filtering procedure.

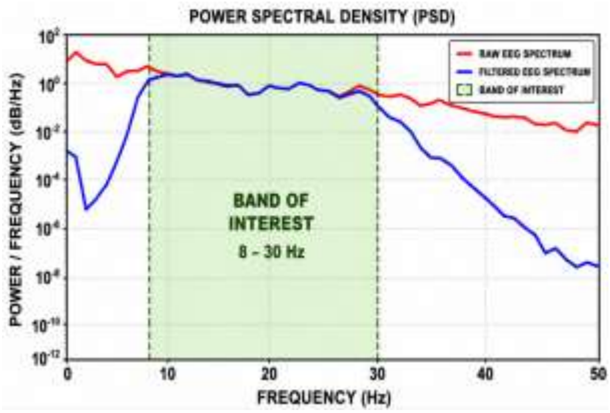

Fig. 2. Power Spectral Density (PSD) of Raw and Filtered EEG Signal

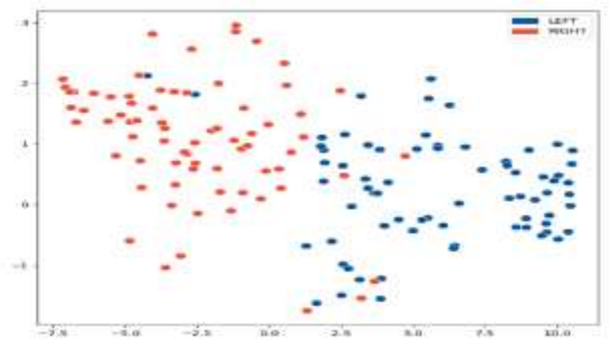

Fig. 3. Feature Distribution of Left and Right Motor Imagery EEG Signals

Figure 3 shows the extracted EEG characteristics divided into two dimensions: the LEFT (blue) and RIGHT (red) motor imagery classes. The fact that the two groups cluster separately with little overlap suggests that the traits that were retrieved adequately separate the classes. The clear distribution increases the capability of the classifier to correctly classify left and right motor imagery tasks, leading to better overall BCI decoding performance.

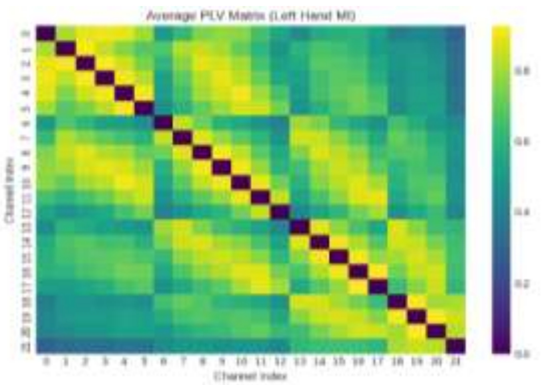

Fig. 4. Average PLV Matrix for Left-Hand Motor Imagery EEG Signals

Figure 4 shows the average motor imagery task functional connectivity matrix for the left hand in terms of PLV. The more strongly connected pairs of channels are shown in yellow, while the less strongly connected pairs of channels are shown in blue. Coordinated neural interactions that convey discriminative information for motor imagery are observed as a result of the connectivity patterns.

B. Data Pre-processing

The BCI Competition IV Dataset 2a was used for data preparation, including concatenation, cleansing and feature engineering. Pre-processing tasks involved artifact removal, signal filtering, suppression of high-frequency noise, data labelling, and normalization to enhance the quality of the signals and ensure consistency for further feature extraction and classification. The main preprocessing procedures are summarized as follows:

- **Artifact Removal:** Duplicates can be removed from the data range using the Remove Duplicates feature on spreadsheet software such as Microsoft Excel and Google Sheets, by selecting the range of data, and then choosing Remove Duplicates on the Data tab specifying which columns to check.
- **Signal filtering:** The main component of MI-EEG was located in the frequency band of the μ rhythm and β rhythm mentioned above. Data were processed with the bandpass filter.
- **High-Frequency Noise Removal:** Unwanted high-frequency noise above the Motor Imagery frequency range (above 20 Hz) discarded components.
- **Label Encoding:** The dataset was prepared for use with ML algorithms by converting categorical variables into numerical values using label encoding. These variables may have included assault kinds or class labels.

C. Data Augmentation

Data augmentation was carried out by creating 2-second EEG segments that overlapped by 50% from each trial in order to enhance model generalizability and decrease overfitting. This method preserved the temporal properties of motor imagery signals while increasing the amount of training samples. The augmented dataset enhanced the diversity of EEG patterns, enabling the proposed DL model to learn more robust and discriminative features.

D. Z-Score Normalization

The goal of data normalization is to make the data more consistent by transforming or standardizing it. The most popular techniques for normalizing data include rescaling, z-score normalization, and min-max normalization. This study employed the z-score normalization approach, which has a mean of 0 and a standard deviation of 1. By applying the Z-score approach, the EEG data from a single motor imagery exercise were normalized. The following is the normalization Equation (1)

$$X^{t}_{normalized} = \frac{X^{t} - \min(X)}{max(X) - \min(X)} \quad (1)$$

The long-term EEG signal is broken down into a sequence of time windows of fixed duration, and each of the time windows is fed into the pulse encoder as a sample.

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E. Data Splitting

The data set was randomly split into training and test sets following a 70:30 ratio with stratification. This allowed for a class distribution in both subsets to be proportional to the original dataset, thereby minimizing sampling bias and the evaluation of the model's reliability.

F. Proposed Deep neural network (DNN) Model

The DNN is a well-known DL algorithm. The input, hidden, and output layers of a DNN network are all completely connected to one another. Each neurone is linked to all the neurones in the layer below it but not to any neurones in the layer above or below it. After each network layer, an activation function is applied to the output to increase the effect of network learning. Thus, DNN may alternatively be considered as a huge perceptron made up of multiple smaller ones. Consider the following formula for the forward propagation computation of the ith layer Equation (3):

$$x_{i+1} = \sigma(\sum w_i x_i + b) \tag{2}$$

where x denotes the input value, w the weight coefficient matrices, and b the bias vector. As an activation function, ReLU is commonly employed in multi-class networks; the formula for this is Equation (4):

$$\sigma(x) = max(0, x) \tag{3}$$

The loss function, which evaluates the output loss of training samples and establishes the network's structure, optimises the backpropagation of the network. The following formula describes the most common loss function used in classification tasks: cross-entropy Equation (5):

$$C = -\frac{1}{N}\sum_x \sum_{i=1}^{M}(y_i log p_i) \tag{4}$$

where N is the number of input data sets, M is the number of categories, yi is the likelihood that the classification i matches the actual category, and ki is the probability of forecasting into category i. The proposed RNN-based EEG model uses the Adam optimiser with a learning rate of 0.001 to guarantee consistent convergence during training. To assure successful learning of temporal EEG patterns, the batch size is set to 32 and the model is trained for 100 epochs. A hidden layer size of 128 units and a dropout rate of 0.5 are used to improve generalisation and capture sequential dependencies in EEG data.

G. Evaluation metrics

The effectiveness of the suggested design was tested using different performance indicators. The categorisation results were first displayed using a confusion matrix that showed the distribution of accurate and inaccurate predictions across several classifications. This matrix was used to gather the True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN) values. Based on these parameters, the following key evaluation parameters were calculated: ACC, PRE, REC and F1 (see below):

1) Accuracy

Fraction of the total number of samples in the dataset (input) that are correctly classified by the trained model. It is given as Equation (3)-

$$Accuracy = \frac{TP+TN}{TP+Fp+TN+FN} \tag{5}$$

2) Precision

The ratio of properly predicted positive cases to total positive examples is known as the ACC of a model's predictions. It suggests PRE. The classifier's ACC in predicting positive classes can be expressed as Equation (4)-

$$Precision = \frac{TP}{TP+FP} \tag{6}$$

3) Recall

This statistic represents the percentage of accurately anticipated positive events in relation to the total number of cases that should have been positive. The formula for it in mathematics is Equation (5)-

$$Recall = \frac{TP}{TP+FN} \tag{7}$$

4) F1 score

It aids in striking a balance between the two variables—REC and PRE —by combining the harmonic mean of the two. The possible values are between zero and one. The formula for it in mathematics is Equation (6)-

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{8}$$

IV. RESULTS AND DISCUSSION

An 80 GB RAM, NVIDIA GeForce RTX 3060 Ti GPU, and 11th generation Intel® CoreTM i7-11700 CPU (2.50 GHz) were the components employed in the DELL Microserver that was submitted to the testing. Python 3.8 was the primary programming language, and scikit-learn 0.21.2 and TensorFlow 2.9 were used to create the machine learning models.

A. Results and Performance Evaluation

The experimental setup and performance evaluation of the suggested Recurrent Neural Network (RNN) model for accurate EEG signal decoding in a brain-computer interface (BCI) are provided in this section. There were a number of classification measures used to measure the model's performance and dependability, including REC, ACC, PRE, and F1. The results of the suggested RNN are displayed in Table II; it attained an ACC of 94.7%, PRE of 94.9%, REC of 94.0%, and an F1 of 94.8%. The results show the good classification performance, predictive performance and suitability for motor imagery-based BCI application of the model.

TABLE II. CLASSIFICTION RESULTS OF PROPOSED MODEL FOR ACCURATE EEG SIGNAL DECODING USING A BRAIN-COMPUTER INTERFACE

Matrix	Recurrent Neural Network (RNN)
Accuracy	94.7
Precision	94.9
Recall	94
F1-score	94.8

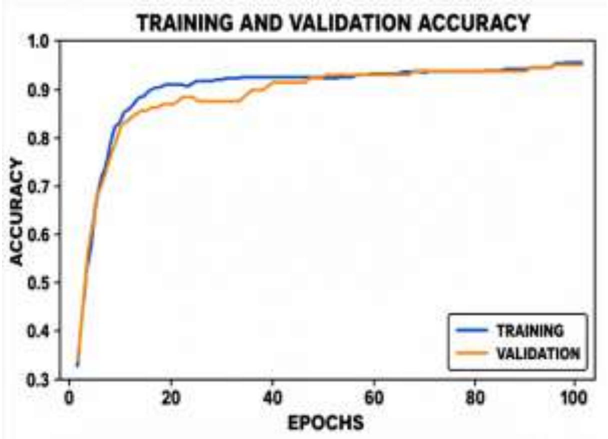

Fig. 5. Accuracy Curve for the proposed Model

The ACC of the proposed RNN during training and validation over 100 epochs is shown in Figure 5. Stable learning, effective model convergence, and little overfitting are indicated by the constant growth and convergence of both curves at around 95% ACC. The close alignment of the training and validation curves demonstrates the model's excellent generalizability for precise EEG signal decoding in BCI applications.

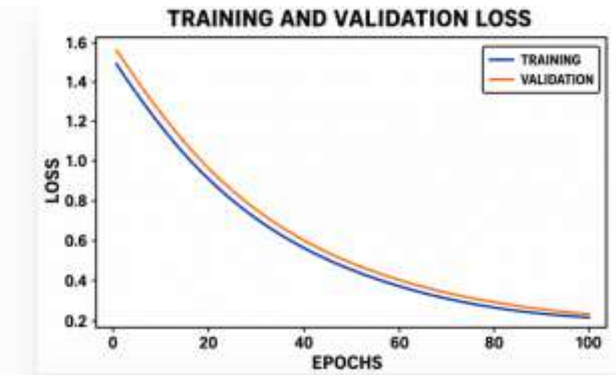

Fig. 6. Loss Curve for the proposed model

The suggested RNN loss curves for training and validation across 100 epochs are shown in Figure 6. Learning is successful, optimization is steady, and model convergence is good since both loss curves converge to a small number. There appears to be little overfitting and good generalizability in the model for reliable EEG signal decoding in BCI applications, as shown by the tight agreement between the training and validation losses.

B. Comparative analysis

Table III offers a comparison of the suggested model's ACC with other models found in the literature. This evaluation is done to assess the model's efficacy. With a total of 94.7% ACC, 94.9% PRE, 94.0% REC, and 94.8% F1, the suggested Recurrent Neural Network (RNN) surpassed all other models. For accurate EEG signal decoding in brain-computer interface (BCI) applications, the suggested RNN model outperformed TCFormer Fusion, SNN, ATCNet, and CNN, which had accuracies of 75.0%, 77.58%, 84.22%, and 81.2%, respectively, in terms of classification performance and resilience.

TABLE III. COMPARISON OF DIFFERENT MACHINE LEARNING AND DEEP LEARNING MODELS FOR ACCURATE EEG SIGNAL DECODING USING A BRAIN-COMPUTER INTERFACE

Model	Accuracy	Precision	Recall	F1-score
TCFormer Fusion[30]	75	-	-	74
SNN[31]	77.58	-	-	-
ATCNet[32]	84.22	-	-	-
CNN[33]	81.2	82	81	83
RNN	94.7	94.9	94	94.8

The suggested Recurrent Neural Network (RNN) was the best at classifying things, with a score of 94.7%. It did better than all the other models tested in this study. Thanks to its exceptional capacity to learn complicated temporal patterns, it is able to read EEG data with remarkable PRE. The enhanced performance demonstrates the suggested model's resilience and dependability, making it a viable strategy for precise BCI applications.

V. CONCLUSION AND FUTURE STUDY

The signals recorded by an electroencephalogram (EEG) are inherently nonlinear and chaotic. The decoding of brain states for identification and classification applications, especially in brain-computer interfaces (BCIs), is hindered by this, though. Newer BCI systems aim to identify both linear and nonlinear aspects of signals. The ACC of categorization may be compromised, nevertheless, as these methods fail to capture the inherent chaos in EEG data. The RNN model using the experimental results obtained the highest ACC rate, which is 94.7%, compared with TCFormer Fusion (75%), SNN (77.58%), ATCNet (84.22%), and CNN (81.2%). This suggests that recurrent architectures perform better in learning temporal dependencies and dynamic patterns in EEG signals for MI decoding. In conclusion, the comparative analysis highlights that DL models, particularly those using RNNs, offer better performance in accurately classifying EEG signals for BCI applications.

The proposed model is constrained by the reliance on a single dataset, potentially impacting generalization to real-world EEG signals. It also requires relatively high computational cost due to sequential processing in RNN. Future work will be focused on further enhancing the ability of the cross-subject adaptability with transfer learning, and designing lightweight hybrid models for real-time BCI applications.

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