International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING

ISSN:2147-6799 www.ijisae.org Original Research Paper

Enhancing Motor Imagery Classification with Deep Learning: A Focus on Dimensionality Reduction and Temporal Features

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Submitted: 01/11/2023 **Revised**: 20/12/2023 **Accepted**: 02/01/2024

Abstract: The Brain-Computer Interface (BCI) system empowers users to communicate with their environment solely through intent, eliminating the need for muscle reactions. However, Electroencephalography (EEG) datasets are typically small and complex due to cumbersome recording processes. This research aims to provide communication capabilities to individuals with complete paralysis, brain stroke disorders, or those who rely on wheelchairs. EEG signal acquisition often includes common artifacts, introducing noise. To tackle these challenges, this study employs Independent Component Analysis (ICA) and various deep learning algorithms within the BCI system. The dataset is sourced from BCI competition III, featuring signals related to the imagined movement of the tongue and the left small finger, from 278 instances. The research introduces a classification method that involves extracting essential components using ICA and experimenting with diverse deep learning architectures to identify the most effective model. The novelty of this research lies in the process of identifying critical components and integrating them into the deep learning network. A comparative analysis is conducted to contrast classification outcomes with and without dimensionality reduction through ICA. Different deep learning models, including Long Short-Term Memory, Gated Recurrent Unit, and Convolutional Neural Network, are employed to enhance EEG signal processing and classification accuracy compared to traditional classification methods. Experimental results indicate that the Convolutional Neural Network combined with ICA achieves the highest accuracy at 89% with the decrease in hidden layers.

Keywords*- Brain computer interface (BCI), Deep Neural network, Feature extraction, Long short term Memory (LSTM), Gated Recurrent Unit (GRU) and Independent component Analysis(ICA).*

1. Introduction

Brain Computer Interface (BCI) represents a rapidly advancing research domain that has captured the attention of researchers on a global scale. A BCI system empowers users to communicate with their environment solely through their intentions, by passing the need for any engagement of nerves or muscles. This technology opens up the intriguing possibility of direct person-to-person communication and serves as an innovative tool allowing individuals to convey instructions to electronic devices through their brain activities. Mainly, BCI systems find application in the management of individuals facing severe neurological conditions such as epilepsy, dementia, and sleep disorders, where these devices can take on the role of electrical controllers.

The core essence of a Brain-Computer Interface lies in its capacity to perceive human intentions and translate them into actions on a computer or other suitable devices. An invasive or non-invasive BCI is a device that measures brain activity. Invasive BCIs necessitate the placement of electrode chips within the skull, while non-invasive systems position sensors externally on the scalp. Non-invasive BCIs offer the advantage of circumventing health risks and the ethical concerns associated with invasive methods. They are the preferred choice for typical users who do not face extreme medical conditions.

An essential part of non-invasive BCIs is the EEG capturing mechanism, which consists of electrodes, amplifiers, an analog-to-digital (A/D) converter, and a recording device. Electrodes capture signals from the scalp, which are then processed by amplifiers to increase the amplitude of EEG signals, facilitating more accurate digitization by the A/D converter. The resulting data can be displayed on a personal computer or similar device for further analysis and interaction. A typical BCI system is the combination of the following steps:

1.The process of capturing signals from the brain's skull or scalp through specialized sensors.

2.Analyzing the digital signal to extract relevant features.

Converting the extracted features into actionable information.

3.Utilizing Brain-Computer Interface (BCI) applications to issue commands to the brain based on the processed signals.

In EEG-based Brain-Computer Interfaces (BCIs), signals are recorded using different strategies to detect user intention. These strategies can vary depending on the presence or absence of external stimuli that evoke user

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intent. One popular paradigm for EEG-based BCIs is motor imagery (MI), in which users imagine specific body movements. MI allows users to operate the BCI solely through their own will, without the need for external stimulation.

It's important to note that the cranial nerves mentioned do not directly relate to EEG-based BCIs. They are responsible for various sensory and motor functions in the head and neck region but are not directly involved in the EEG signal recording process. EEG aims to record the brain functions electrically by applying electrodes to the scalp to detect brainwave patterns. These brainwave patterns are then used to interpret the user's intentions for BCI control. The cranial nerves and their functions are distinct from EEG-based BCI technology. [1][2].the table shows brain rhythm with corresponding frequency and the brain state.

This research demonstrates how the ICA and Deep Learning model EEG signal. By applying the algorithm to these specific problems, the study highlights its potential for enhancing decision-making processes in dataset. The workflow of this article is as follows: Section 2 lists the relevant literature. The data description is explained in Section 3. The suggested technique is explained in Section 4, outcomes and debates are explained in Section 5, and the study is concluded with opportunities for more research in Section 6.

Table 1: Brain rhythm with corresponding frequency

Frequency band	Frequency	Brain state
Delta	0-4 HZ	Sleep
Alpha	8-12Hz	Relax, external attention
Theta	4-7Hz	Deep relaxed, inward focus
Beta	13-35Hz	Very relaxed, passive attention

2. Related Works

RajdeepChatterjee et al [3] conducted a comparative study involving the extraction of wavelet energy-entropy features from different frequency bands using both overlapping and non-overlapping techniques. They compared four distinct extraction approaches:The first approach involved segmenting each trial individually. The second approach entailed dividing each trial into three segments.The third approach divided each trial into five frequency bands.The fourth approach segmented each trial into four frequency filter bands.The features extracted through these methods were subsequently subjected to classification using various algorithms, including K-Nearest Neighbors, Support Vector Machines with different kernel functions, and Mix Bagging. The study's conclusions demonstrated that the recommended strategy was effective and achieved an accuracy rate of 91.43%.

HamidrezaAbbaspour et al [4] has proposed hybrid genetic algorithm. In feature extraction three type of features are extracted from Graz 2003 and Graz 2005 data set. These features include temporal, spectral, and wavelet-based features, with each type comprising 10 features, resulting in a total of 30 features. The most pertinent characteristics were chosen using a genetic algorithm after the feature extraction procedure. A Support Vector Machine was then employed for the categorization process. The results of this study produced a classification accuracy of 92.14% for the Graz 2003 dataset. For the Graz 2005 dataset, the achieved classification accuracies were 89%, 84%, and 85%.

Xiaozhonggeng et al [5] haveused combination of Independent Component Analysis, wavelet and common spatial patterns for feature extraction. Then the features are classified using Bagging tree, SVM, LDA, Bayesian LDA and attained respective accuracy of 0.79%,0.81%,0.78%,and 0.87%.

Jingshan Huang et.al [6] has introduced a method where EEG wave signals were segmented into sub-signals. The extracted features were subsequently subjected to classification using sparse representation and fast compression residual convolutional neural networks (FCRes-CNN). Furthermore, FCRes-CNN obtained a remarkable accuracy rate of 98.82%, outperforming the sparse representation approach. Extracted features are classified using sparse representation and fast compression residual convolution neural networks. FCRes-CNN is gave the better result as 98.82% compared to SR.

SihengGao et.al [7] focused on the reconstruction of EEG signals to optimize data size. They employed a combination of the Gated Recurrent Unit and Convolutional Neural Network algorithms to decode and classify the signal into different classes. Using a parallel structure for feature fusion, they achieved a classification accuracy of 80.7%. This approach effectively combined the strengths of GRU and CNN to interpret the EEG signal data.

Swati Gawhale et.al [8] has used Power Spectrum Density (PSD) dataset of patients with sliding sleeping disease. In pre-processing removal of artifacts of the signals and feature extraction are done by using power spectral density. Finally detection of sleep stage is done using hybrid convolution neural network and ensample neural network with impressive accuracy of 96.78%.

Thus, the primary objective of the proposed study is to put a number of data mining approaches into practice in order to create an automated and effective diabetes diagnosis system. The best possible feature selection for the classifier's training is then achieved by applying an Intelligent Harris Hawks Optimizer (IHHO) approach. Apart from 5G, several other essential issues need to be resolved, including as enhanced quality of service (QoS), faster data speeds, and expanded scheme capabilities [15].

This readable essay explores the state of future 6G wireless technologies. There includes discussion of emerging technologies including optical wireless technology and artificial intelligence. Mobile networks should speed up to a hundred times quicker with 6G [16].

3. Data Description

For an experimental data analysis, we employed the dataset provided by the University of Tubingen of Technology, specifically BCI Competition III, Data Set –Ia, focusing on motor imaginary ECoG recordings with session-to-session transfer. In this dataset, subjects engaged in imagined movements of their left small finger or tongue. During these trials, an 8x8 ECoG platinum electrode grid was implanted on the contralateral (right) motor cortex to capture the electrical brain activity time series. Both training and test data were collected for the same subject performing the tasks, with all recordings consistently sampled at a rate of 1000Hz. Each trial involved the recording of imagined tongue or finger movements over a 30-second period, with a time interval of 0.5 seconds between each sample.

The training dataset comprises 278 trials, each providing 64 channels of information, and each trial contains 3000 samples. Importantly, each trial in the training data is associated with a specific label denoting the type of movement.

Conversely, the test dataset consists of 100 trials, but notably, these trials lack associated labels. This dataset serves as a critical component for assessing and testing the effectiveness of models and algorithms in classifying motor imagery based on the recorded brain activity.

4. Proposed Method

Our proposed method consists of taking only the convergence components in ICA by identifying the tolerance factor and maximum number of iterations necessary for convergence. Then only the extracted components are passed to the below mentioned neural networks to analyses the performance. Experiment is also conducted with different hidden layers, optimizers and learning rate. The deep learning architecture which maximizes the accuracy is proposed.Figure 1 shows the flow of the methodology described in this section.

4.1 Data Alignment

This dataset is available in .mat format which contains two components X and Y.X Contains 64 channel information for 278 trails and Y contains the Target values. Initially the dataset is three dimensions in nature so to ease the process the three dimension data is converted into two dimensional. All Channels information is passing as an input so each trial has 64 * 3000 = 192000 data.

4.2 Dimensionality Reduction

Independent Component Analysis is a valuable technique in the field of BCI, where it is used for separating and analyzing the neural signals recorded from the brain. ICA plays a crucial role in BCI for various applications, including dimensional reduction. ICA can also enhance the quality of recorded EEG data by separating the sources of noise and interference, ICA helps in improving the signal-to-noise ratio, making it easier to detect and analyze the neural signals of interest. In this proposed work 60 significant components are selected with tolerance value of 0.1 and the maximum iteration taken for consideration is 200.

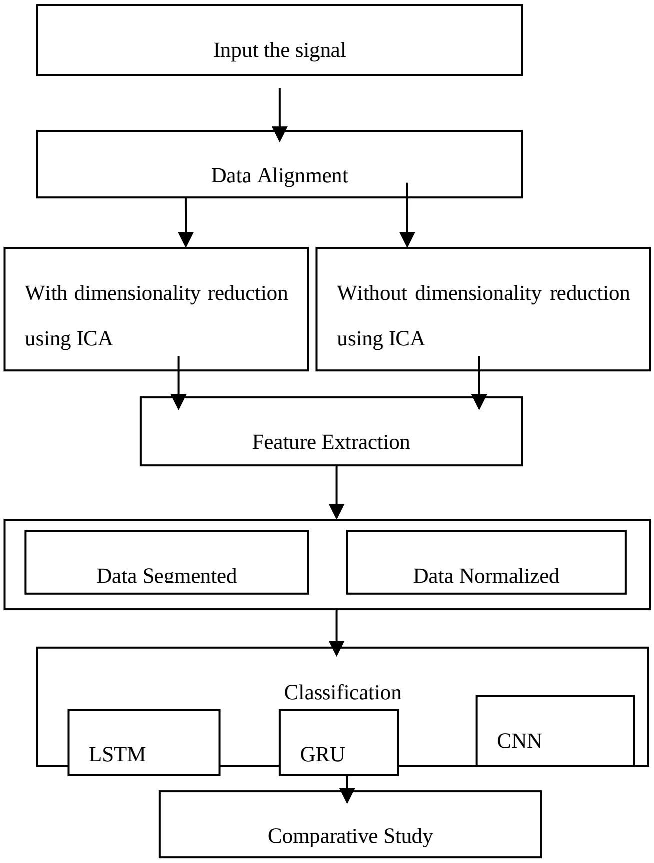

Fig 1: Structure of process

4.3 Feature extraction

Feature extraction is a critical step in processing EEG signals, particularly in the context of BCI systems. This step significantly impacts the effectiveness of the BCI. It involves reducing the dimensionality of raw signals and applying various techniques to extract informative features from both the raw and pre-processed signals.

In this proposed approach, both the raw signals and the reduced-dimension signals undergo feature extraction. The extracted features are chosen for their accuracy and reliability. This approach achieves an optimal balance between temporal and frequency resolutions. Unlike methods using sine and cosine functions, the wavelet transform employs finite basis functions known as wavelets. These wavelets are represented by finite-length waveforms. The wavelet transform essentially represents the original input signal as a linear combination of these fundamental functions. This technique offers a powerful means of feature extraction and representation in EEG signal processing.

4.4 Temporal feature extraction

Temporal feature had specified time slot for implementation. Signals are calculated within the predefined time slot according to that necessary features are collected in the time window. Once the features are generated they are linearly scaled.

4.5 Data Segmentation

Data segmentation is a technique of splitting a data into homogenous group. Segmentation is the part of the data mining used to clean data and detecting the pattern.

4.6 Normalization

Normalization is also part of data mining technique. In general all the data are in different scale. It adjusts the data's decimal value to standardize it.

5. Classification

Long Short-Term Memory networks represent a specialized type of recurrent neural network distinguished by their proficiency in maintaining information over extended sequences. In contrast to conventional RNNs, which depend solely on previous inputs, LSTMs excel in storing and manipulating data over prolonged periods, employing three pivotal components: the forget gate, the input gate, and the output gate.

When deciding whether information inside the cell state should be kept or deleted, the forget gate plays a crucial function. It assesses the prior hidden state and current input, utilizing a weighted mechanism to selectively erase or retain information in the cell state.

Responsibility for deciding which new information should be integrated into the cell state lies with the input gate. Similar to the forget gate, it relies on the prior hidden state and current input to calculate updates to the cell state, serving as the mechanism for adding or updating information within the cell state.

The output gate governs the composition of the next hidden state, combining the current input, previous hidden state, and updated cell state to generate the new hidden state. The transfer of data from the cell state to the final output may be managed by the LSTM due to this gate.

LSTMs leverage various activation functions, including the sigmoid function and hyperbolic tangent (tanh) function, to compute values associated with gates and updates to the cell state. These activation functions play a pivotal role in shaping how information is stored, retained, and transmitted within the LSTM network, making it a potent tool for managing and processing sequential data.

Gated recurrent Unit

The structure of Gated Recurrent Units (GRUs) parallels other recurrent neural networks (RNNs) by featuring a hidden state that encapsulates the network's memory of past time steps. This hidden state undergoes continuous updates at each time step, serving both as the output for the current step and as the input for subsequent steps. A distinctive feature of GRUs is the inclusion of an update gate, characterized by a value between 0 and 1.This gate is essential in deciding how much of the prior concealed state is kept in place and how much of the new candidate state affects the present time step. A value of 0 signifies complete dismissal of the previous state, while a value of 1 indicates full retention. Additionally, GRUs incorporate a reset gate, responsible for governing the extent to which the preceding hidden state is discarded during the calculation of the candidate state for the current time step. Every time step, the candidate state is calculated using the reset gate, the prior concealed state, and its recent input. This candidate state encapsulates new information intended for integration into the hidden state.

The resultant current hidden state is a blend of the preceding hidden state and the candidate state, with the update gate dictating the optimal balance between these components. This intricate gating mechanism empowers GRUs to effectively manage information flow, selectively retaining pertinent past states while integrating new information based on the prevailing context.

Convolution Neural Network

Neural Convolution Network Convolution Neural Networks are mostly utilized in classification to determine the degree of data correctness. It is widely used for many kinds of applications. The primary work of CNN is to train the dataset to make the computer learn to predict the input. Generally, CNN has four following steps. They are,

a. Input Layer

b. Convolution Layer

c. ReLU Layer

d. Max pooling Layer

e. Fully Connected Layer

f. Soft Max

The input layer consists of data given to the CNN architecture for the entire process. The data is processed as an input in way of representing the matrix. It is the initial working progress of the artificial neural networks and also it is the combination of many neurons which can be applied further too the neural network layers. Weights and Bias are calculated in the neuron layer because of it is the first ever layered that sends the data to the other layers. The hidden layer is the middle process of the input layer and output layer.

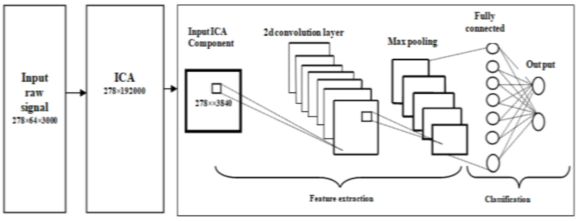

Fig 2: Architecture of proposed Convolution Neural Network

Figure 2 shows the full working architecture of Convolutional Neural Networks with Input layers, ReLU and soft max functions, concluded with a fully connected layer. Neurons will calculate the input weights and it will give the output result over the activation function. Sometimes weights are assigned randomly but, in some cases, weights are assigned with some calculations is called as back propagation. In back propagation has to update the weights and delta values. A feed-forward neural network works as a single-chain model whereas the information is taken over from the input nodes through the hidden nodes to the output nodes. Any other loops are not followed in the feed-forward neural networks. The output layer is the last processing layer of neurons that gives the final result. A fully connected layer is obtaining the input data that will send to the other connected layers on the basis of classes. Output is obtained by extracting the features of the data defining classes for the dataset. Convolution layers help to pass the information to input layers. This layer receives the data from the input layer and also each and every neuron layer will get the data by passing one to another layer.

Classifier	Train (l)	Train (Acc)	Test (l)	Test (Acc)	Best (Acc)
LSTM	0.03	0.92	0.46	0.87	0.87
GRU	0.24	0.97	0.62	0.80	0.80
CNN	0.00	1.0	0.45	0.89	0.89

6. Result and Discussion

The current analysis highlights the utilization of an intelligent deep learning-based approach to identify the most crucial information within the BCI system. The proposed system improves the efficiency of the EEG signal. ICA is used to improve the quality of the original EEG signal while simultaneously reducing the data dimension. For each trail in channel 60 components are selected. With the dimensionality reduction and without reduction data are extracted. Then temporal based features are extracted in the time window and extracted feature are segmented. The segmented data are scaled using the normalization technique and reshaped the original data. Split the array of the data 278×64×3000 for train and test. Three types of classifier are used for classification.

LSTM, GRU, and CNN are recurrent neural networks. In prior research, artificial neural networks yielded the best results, prompting our transition to deep learning. LSTM recurrent neural networks utilized L2 norm regularization and cross-entropy loss functions, updated through backpropagation gradient descent. The Adam optimizer proved to be the most effective for all deep networks, including the GRU network. CNN was particularly adept at class identification, employing a Sequential 2D convolution network. The learning rate for this network was set to 0.001, with an L2-norm regularization coefficient of 0.01.

Table 2 illustrates the training and accuracy testing results for each classifier before dimensionality reduction. The training accuracy for the LSTM classifier was 0.98, the test accuracy was 0.76, the loss was 0.0953, and the test loss was 0.4827. The GRU network scored 0.985 training accuracy, 0.8471 test accuracy, 0.0673 loss, and 0.8471 test loss. CNN had the best accuracy among them, with a test accuracy of 0.87, as shown in Figure 3.

Table3 presents the results after dimensionality reduction. A comparison between the two tables indicates that dimensionality reduction significantly improved the accuracy of the data. For LSTM, training loss reduced to 0.0356, and testing loss was 0.4656. GRU achieved a training loss of 0.2412 and a test loss of 0.6217, while CNN had a training loss of 0.0060 and a test loss of 0.4571. Overall, classifiers demonstrated improved accuracy after dimensionality reduction, with CNN achieving the highest accuracy of 0.89 and it is illustrated in Figure 4.

Table 2: Train and Test Accuracy for the classifiers before dimensionality reduction

Classifier	Train (l)	Train (Acc)	Test (l)	Test (Acc)	Best (Acc)
LSTM	0.09	0.98	0.48	0.76	0.78
GRU	0.06	0.98	0.56	0.84	0.84
CNN	0.02	1.0	0.36	0.87	0.87

l - loss Acc - Accuracy

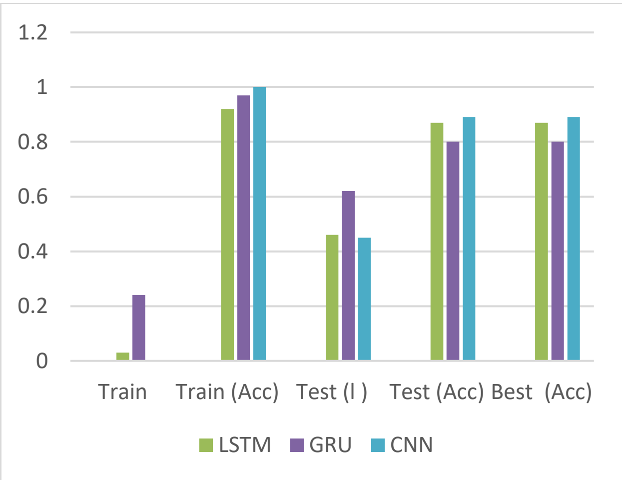

Fig 3. Train and Test Accuracy for Classifiers after dimensionality reduction

The model exhibits successful learning from both the training and testing datasets, with performance evaluation based on validation metrics such as precision, recall, and F-score. Table 4 and 5presents the average accuracy scores for the LSTM, GRU, and CNN classifiers and it is graphically plotted in Figure 5 & 6.

$$\text{Accuracy} = \frac{(TP + TN)}{(TP + FP + TN + FN)}$$

Table 4: Validation Measure for Before Dimensionality Reduction

Classifier	Precision	Recall	F1-Score
LSTM	0.66	0.64	0.64
GRU	0.71	0.67	0.67
CNN	0.83	0.82	0.82

l - loss Acc - Accuracy

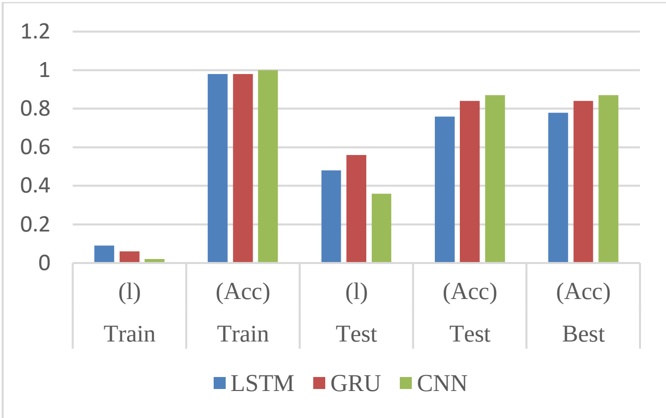

Fig 4. Train and Test Accuracy for Classifiers before dimensionality reduction

Table 5: Validation Measure for After Dimensionality Reduction

Classifier	Precision	Recall	F1-Score
LSTM	0.86	0.86	0.86
GRU	0.75	0.77	0.75
CNN	0.80	0.89	0.85

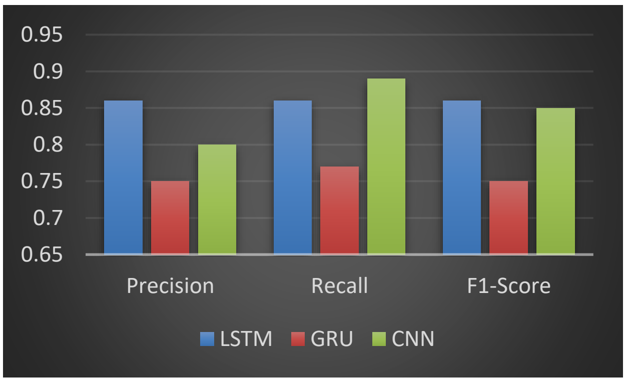

Fig 5. Validation measures for before ICA

Fig 6. Validation measures for after ICA

7. Conclusion

A Brain-Computer Interface (BCI) system plays a crucial role in accurately categorizing various patterns of brain signals, allowing users to perform distinct mental tasks. In the context of this BCI dataset, two imaginary movements, involving the tongue and the left small finger, are considered. This research introduces an optimized approach for EEG signal feature extraction and classification, employing Independent Component Analysis and deep learning models. Different neural network architectures were explored, including LSTM, GRU, and CNN. Ultimately, the combination of ICA with Convolutional Neural Network achieved the highest accuracy. The optimal results were obtained by setting the ICA tolerance factor to 0.1 and conducting 200 iterations. In the deep learning architecture, the model used 128 hidden layers and employed a learning rate of 0.1. The number of hidden layer employed after dimensionality reduction is only 10. Validation metrics such as precision, recall, and F1-score were utilized to calculate the average accuracy rate for each algorithm. CNN emerged as the top performer, achieving an impressive 89% accuracy. This research demonstrates the efficacy of ICA and deep learning in enhancing the classification of EEG signals for BCI applications.

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