Integrating EEG Artifact Removal with Deep Learning for Accurate Motor Imagery Classification in Acute Stroke

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ABSTRACT

Nowadays, the number of stroke incidents has increased, particularly in aging populations and areas with limited access to healthcare. This rise has highlighted the need for innovative assistance solutions to improve the quality of life of stroke survivors. This study aimed to address the challenges of noisy and artifact-laden Electroencephalogram (EEG) data by employing preprocessing with autonomous and semi-autonomous artifact removal techniques, including the use of EEGLab. This study focuses on the classification of EEG data for stroke patients using Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNNs). Combining the strengths of CNNs and LSTMs, a hybrid model leverages both spatial and temporal features of EEG data to improve classification accuracy. The hybrid CNN-LSTM model outperforms individual CNN and LSTM models in classifying motor imagery tasks, demonstrating its potential for robust brain-computer interface applications in stroke rehabilitation. This integrative approach not only improves classification performance but also sets the stage for more effective therapeutic interventions, ultimately aiming to enhance patient outcomes.

Keywords-EEG; stroke patients; artifact removal; CNN; LSTM; hybrid model; brain-computer interface

I. INTRODUCTION

According to recent epidemiological studies, the incidence of strokes has increased in the last few decades, particularly in aging populations and regions with limited access to preventive healthcare [1, 2]. This rise has underscored the urgent need for innovative solutions to improve rehabilitation outcomes for stroke survivors [3]. Stroke survivors often face significant challenges in controlling assistive devices, such as wheelchairs, due to motor impairments resulting from their condition [4]. These difficulties can seriously impact their quality of life, limiting their independence and mobility [5]. Traditional rehabilitation methods sometimes fail to address these issues comprehensively, necessitating the exploration of advanced technologies to bridge this gap and provide better support for stroke patients [6]. Electroencephalography (EEG) offers a promising avenue, enabling new methods to assist stroke survivors through Brain-Computer Interfaces (BCIs) [7].

This study focuses on the classification of Motor Imagery Electroencephalography (MI-EEG) signal data from stroke patients [8] using Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNNs) [9, 10]. Accurate classification of motor imagery tasks from EEG signals is crucial to advance the development of effective BCI systems [11]. Such systems can significantly improve the ability of stroke survivors to control assistive devices through brain signals, bypassing impaired motor pathways [12]. This approach builds on the existing body of research, leveraging the capabilities of EEG to address a critical need in stroke rehabilitation.

Current state-of-the-art research has extensively explored the use of various machine learning techniques for the classification of EEG signals [13-15]. Previous studies have demonstrated the potential of deep learning models, such as CNNs and LSTMs, in capturing complex patterns in EEG data [16-20]. Among these, CNNs have shown superior performance in spatial feature extraction, while LSTMs excel in handling temporal dependencies in time-series data [21-23]. However, most existing solutions focus solely on either CNNs or LSTMs, rarely combining their strengths to improve classification accuracy. Additionally, preprocessing EEG data using tools like EEGLab for artifact removal, Power Spectral Density (PSD) analysis, and Event-Related Desynchronization (ERD) assessment is crucial, but often underemphasized. To overcome these limitations, this study presents a hybrid approach that integrates these advanced techniques.

The main limitation of current approaches is their suboptimal performance when dealing with the noisy and artifact-laden nature of EEG data from stroke patients. This study aimed to address this limitation by systematically comparing the performance of CNNs and LSTMs, both individually and combined, to identify the most effective model for EEG classification. In addition, advanced preprocessing techniques are employed, including the use of the Multiple Artifact Rejection Algorithm (MARA), Semi-Automated Selection of Independent Components for Artifact Correction (SASICA), and Eyes and Muscle Artifact Removal (EMAR), are employed to enhance the quality of the EEG data before analysis [24-27]. Through these enhancements, this study sought to develop a more accurate and reliable system for classifying EEG signals in stroke rehabilitation.

The study involved EEG data from 50 acute stroke patients performing motor imagery tasks. The data were preprocessed using EEGLab, which includes filtering, re-referencing, Independent Component Analysis (ICA) for artifact removal, and visualizations such as heat maps and topographical plots. Advanced artifact detection and removal techniques, including MARA, SASICA, and EMAR, were performed using ICLable. The cleaned and processed data were then used to train and evaluate the CNN, LSTM, and hybrid CNN-LSTM models. Performance was assessed based on classification accuracy and other relevant metrics. The results suggest that the combination of CNN and LSTM can effectively harness both spatial and temporal features in the EEG data, leading to improved classification performance.

II. RESEARCH METHODOLOGY

A systematic analysis of brain activity was performed using EEG to determine its correlation with motor functions, specifically hand movements. The process begins with the acquisition of brain signals through EEG. Raw EEG data is then preprocessed to remove noise and artifacts, producing clean time-series data. Preprocessing is crucial as it ensures the quality and reliability of the data for subsequent analysis. The clean data was then visualized to identify distinct patterns of neural activity associated with different motor tasks. Figure 1 provides a visual representation of the entire process. This research process can be outlined as follows:

- Data Acquisition: The motor imagery EEG dataset utilized in this study was obtained from [28] and includes .edf files containing motor imagery event information. Following data collection, EEGLab is employed to analyze and preprocess the data to prepare it for the following phases.

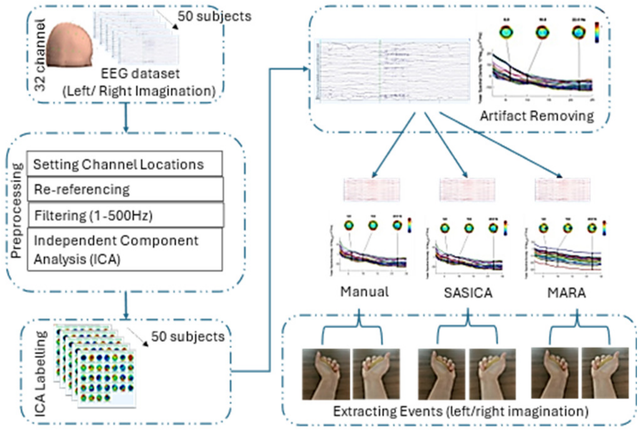

Fig. 1. Research overview.

- Preprocessing: The raw EEG data undergoes a series of cleaning processes to eliminate noise and artifacts. This involves filtering, re-referencing, and employing ICA for artifact removal. Advanced techniques, such as MARA, SASICA, and EMAR, are utilized to ensure the highest data quality. Following this, features are extracted from the cleaned data for further analysis.
- Labeling and Feature Extraction: Labeling is performed to assign categories to the data points, indicating the specific motor imagery task associated with each segment.
- Classification: The extracted features are subsequently used to train neural network models. In this study, both Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks are employed to classify motor imagery tasks. CNNs are proficient in capturing spatial features, whereas LSTMs excel at handling temporal dependencies in the data. Additionally, this study explores a hybrid CNN-LSTM model [29] to leverage the strengths of both approaches.
- Evaluation: The performance of the CNN, LSTM, and hybrid CNN-LSTM models is evaluated based on classification accuracy and other relevant metrics. The objective is to identify the most effective model for accurately predicting hand movements from EEG data.

A. Dataset Description

The dataset was acquired at Xuanwu Hospital, Capital Medical University, Beijing, China, using a wireless 32-channel semi-dry EEG acquisition system (ZhenTec NT1) [30]. It comprises recordings from 50 acute stroke patients within 1-30 days post-stroke who performed standardized left- and right-hand motor imagery tasks [31]. Each participant completed 40 trials, and EEG signals were recorded at a sampling frequency of 500 Hz.

B. EEGLab Study

EEGLab was employed for EEG data processing and analysis. EEGLab is a powerful, open-source MATLAB toolbox designed for the processing of EEG data [32, 33]. The Biosig library was used to facilitate the use of .edf files. Table I presents details on the motor imagery data of one participant.

TABLE I. STROKE EEG DATA INFORMATION

Name	Value	Description
Channels per frame	31	31 EEG electrodes recorded simultaneously
Frames per epoch	160000	160000 times per epoch (Frames per Epoch=Sampling rate × Record Duration)
Epochs	1	1 continuous segment of data.
Events	120	120 specific markers or triggers within the recording (40: instruction events, 40 break events, 20 left motor imagery events, and 20 right motor imagery events)
Sampling rate (Hz)	500	500 samples per second for each channel
Epoch start (s)	0.000	Epoch starts at 0 seconds (beginning of the recording).
Epoch end (s)	320	Epoch ends at 320 seconds (~5min).
Reference	Average	EEG data referenced to the average of all channels to reduce noise.
Channel location	Yes	Locations of the 31 EEG channels are provided.
ICA weights	Yes	Data has undergone ICA for artifact removal and source separation.

C. Setting Channel Location

Electrode localization is vital for the interpretation of EEG data, especially when spatial resolution is essential [34]. The dataset includes the spatial coordinates of EEG electrodes, provided in a .locs file format, which details the (x, y, z) positions of each electrode relative to a standard head model or a specific reference point. Table II provides the spatial coordinates for each EEG electrode, specified in degrees and normalized radial distances.

TABLE II. EEG ELECTRODE PLACEMENT AND COORDINATES

Electrode	Angle	Radial distance	Label	Electrode	Angle	Radial distance	Label
1	-18	0.51111	Fp1	17	90	0.51111	T4
2	18	0.51111	Fp2	18	180	0.12778	CPz
3	0	0.25556	Fz	19	-118	0.27778	CP3
4	-39	0.33333	F3	20	118	0.27778	CP4
5	39	0.33333	F4	21	-108	0.51111	TP7
6	-54	0.51111	F7	22	108	0.51111	TP8
7	54	0.51111	F8	23	180	0.25556	Pz
8	0	0.12778	FCz	24	-141	0.33333	P3
9	-62	0.27778	FC3	25	141	0.33333	P4
10	62	0.27778	FC4	26	-126	0.51111	T5
11	-72	0.51111	FT7	27	126	0.51111	T6
12	72	0.51111	FT8	28	180	0.51111	Oz
13	90	0	Cz	29	-162	0.51111	O1
14	-90	0.25556	C3	30	162	0.51111	O2
15	90	0.25556	C4	31	-43	0.65	HEOL
16	-90	0.51111	T3	32	23	0.71	HEOR

D. Re-Referencing

Initially, the EEG signals were referenced to the CPz electrode. Changing the reference after recording is called re-referencing, which can help reduce noise and improve signal quality. This study employed the Common Average Reference (CAR) method, which is often recommended for obtaining a more balanced representation of cortical activity. In the CAR method, the new reference is the average of the electrical activity measured across all scalp channels. The formula for calculating the re-referenced signal V_i' at electrode i is shown in (1), where V_i is the original signal at electrode i, and N is the total number of electrodes. The transformation can also be expressed as in (2), where V_{ref_online} is the initial online reference (e.g., CPz).

$$V_i' = V_i - \frac{1}{N}\sum_{j=1}^{N} V_j \quad (1)$$

$$V_i' = [V_i - V_{ref\_online}] - \left(\frac{1}{N}\sum_{j=1}^{N} V_j - V_{ref\_online}\right) \quad (2)$$

E. Filtering

Filtering is a critical preprocessing step in EEG data analysis to remove noise and artifacts from the recorded signals [35]. A 0–500 Hz bandpass filter was applied to the EEG data to preserve relevant signals while reducing noise. The bandpass filter can be mathematically represented as in (3), where $y(t)$ is the filtered signal, $x(t)$ is the original EEG signal, and $h(t)$ is the impulse response of the bandpass filter. In the frequency domain, this can be expressed using the convolution equation (4). $Y(f)$ is the Fourier transform of the filtered signal, $X(f)$ is the Fourier transform of the original signal, and $H(f)$ is the frequency response of the filter.

$$y(t) = \int_{-\infty}^{\infty} x(\tau)h(t-\tau)d\tau \quad (3)$$

$$Y(f) = X(f) * H(f) \quad (4)$$

F. Independent Component Analysis (ICA)

ICA is a powerful computational method used in EEG data analysis to separate mixed signals into their underlying independent components [36]. By applying ICA, artifacts such as eye blinks, muscle movements, and line noise can be isolated, facilitating cleaner neural signal analysis. Mathematically, if X represents the observed mixed signals and S represents the independent sources, ICA aims to find an unmixing matrix W as shown in (5). Here, W is calculated so that the statistical independence of S is maximized. ICA was performed using EEGLab.

$$S = WX \quad (5)$$

ICLabel was used, which is an EEGLab plugin to automate the classification of independent components. ICLabel leverages a machine learning model trained on expert-labeled data to classify each component into categories such as brain, muscle, eye, heart, line noise, and channel noise. The ICLabel algorithm calculates the probability P_i that a given component i belongs to each category, providing a probabilistic output that helps in making informed decisions about which components to retain or reject. The classification can be represented as in (6), where z_i is the score assigned to category i and K is the total number of categories.

$$P_i(category) = \frac{e^{z_i}}{\sum_{k=1}^{K} e^{z_k}} \quad (6)$$

Artifact detection and removal are essential steps in EEG preprocessing to ensure data quality and reliability. This study employed a combination of automated and manual methods to identify and eliminate artifacts from the EEG data. MARA is a semi-automatic method for detecting and removing artifacts from EEG data using a machine learning approach [37]. The algorithm involves two primary steps: feature extraction from Independent Components (ICs) and classification of these components. The features used in MARA include kurtosis, spatial average deviation, spatial variance, temporal kurtosis, temporal variance, and others. These features are extracted from each IC to capture various characteristics of the EEG signals. A pre-trained linear classifier, typically using Linear Discriminant Analysis (LDA), then determines whether an IC is an artifact based on these features. The decision function for the classifier can be written as in (7), where w is the weight vector learned from training data, x is the feature vector of an IC, and b is the bias term. The classification decision is made based on the sign of y; if $y > 0$, the IC is classified as an artifact, and if $y \leq 0$, it is classified as a non-artifact.

$$y = w^T x + b \tag{7}$$

SASICA is a semi-automatic method used for selecting artifact ICs to define threshold values for different metrics [37]. These metrics include correlation with Electrooculogram (EOG) channels, power spectrum, signal variance, and kurtosis. The correlation with EOG channels is calculated using (8), where IC is the IC time series and EOG is the EOG signal. The power spectrum, calculated as in (9), helps identify specific patterns indicative of artifacts. Signal variance is given by (10), and kurtosis is given by (11). High values in these metrics often indicate the presence of artifacts. SASICA combines these metrics to provide a composite score, marking components that exceed user-defined thresholds as artifacts.

$$Corr_{EOG} = \frac{Cov(IC,EOG)}{\sigma IC \sigma EOG} \tag{8}$$

$$P(f) = |F(IC(t))|^2 \tag{9}$$

$$\sigma_{IC}^2 = \frac{1}{N}\sum_{i=1}^{N}(IC_i - \mu_{IC})^2 \tag{10}$$

$$Kurt(IC) = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{IC_i - \mu_{IC}}{\sigma_{IC}}\right)^4 \tag{11}$$

EMAR was performed to ensure the highest data quality. This process involves visually inspecting independent components and manually flagging those that represent artifacts. The following MATLAB code snippet illustrates the manual artifact removal procedure using EEGLAB's pop_icflag function.

Matlab Code
EEG = pop_icflag(EEG, [NaN NaN; 0.9 1; 0.9 1; NaN NaN; NaN NaN; NaN NaN; NaN NaN]);
[ALLEEG,EEG,CURRENTSET]=eeg_store(ALLEEG,EEG,CURRENTSET;

G. Dataset Modeling

This study implemented three neural network models for EEG classification: a CNN, an LSTM, and a hybrid CNN-LSTM. The CNN consists of a 1D convolutional layer (64 filters, kernel size 3, ReLU), followed by max-pooling, flattening, a dense layer (50 units, ReLU), and a softmax output layer. The LSTM model includes an LSTM layer with 50 units (ReLU) to capture temporal dependencies, followed by a softmax output. The hybrid CNN-LSTM combines convolutional layers for spatial feature extraction with LSTM layers for temporal learning, ending with a softmax output (Figure 2). All models were compiled with the Adam optimizer, categorical cross-entropy loss, and accuracy as the evaluation metric.

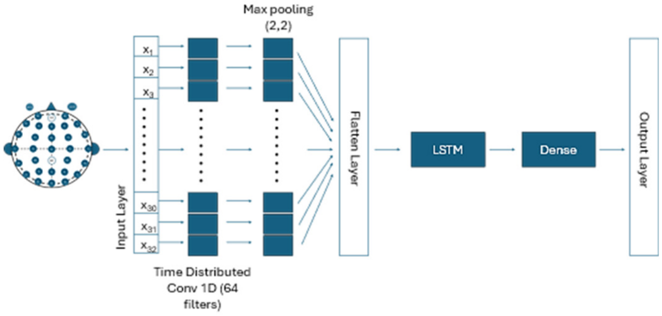

Fig. 2. Hybrid CNN-LSTM Architecture.

III. RESULTS AND DISCUSSION

The results of this study were compared with previous works, including studies that used the same acute stroke motor imagery dataset. In [30], classification accuracies between 55% and 72% were reported, with its best-performing approach (TWFB+DGFMDRM) achieving 72.21%. These results highlight the inherent difficulty of decoding motor imagery in acute stroke patients, where EEG signals are affected by noise, non-stationarity, and variability related to neural impairment. Other works focused on a single preprocessing method or on evaluating CNN or LSTM models independently [29, 38].

MARA, SASICA, and EMAR were applied for artifact removal on the EEG dataset. Each method improves data quality by targeting different types of artifacts. Figure 3 shows EEG traces after MARA, with smoother signals and reduced noise. MARA uses a machine learning approach based on spatial and temporal features, effectively removing eye blinks, muscle movements, and heartbeats. However, aggressive removal can produce overly uniform signals, reducing variability and obscuring differences between cognitive states, such as the strong correlation observed between C3 and C4. SASICA semi-automatically identifies artifacts using multiple criteria, including channel correlations and power spectrum, which is particularly effective at removing eye movement artifacts. EMAR specifically targets eye-blink and muscle-related artifacts, resulting in cleaner signals in affected regions. However, other artifacts may persist.

Figure 4 shows the classification and properties of various independent components extracted from the EEG dataset using the EEGLab toolbox. Each component is represented by a scalp topography plot and labeled with its source type (e.g., brain, heart, channel noise). The topography plots show the spatial distribution of EEG activity, with colors indicating signal intensity and components classified as "Brain," "Heart," and "Noise."

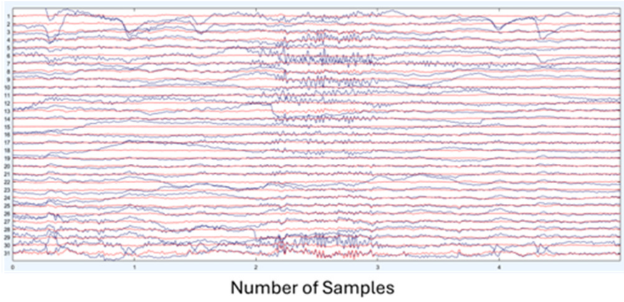

Fig. 3. EEG time series plot after MARA artifact removal.

Figure 5 shows the EEG correlation matrix after MARA, revealing strong correlations, including a value of 1 between C3 and C4, which limits the distinction of directional thoughts due to excessive artifact removal. In contrast, SASICA and EMAR produce more moderate correlations. MARA removes a wide range of artifacts, but performance varies across subjects and models.

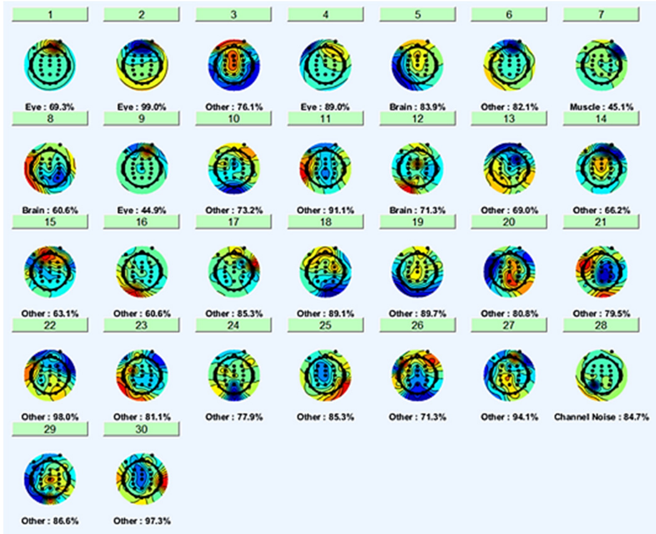

Fig. 4. Visualization of component attributes for one subject.

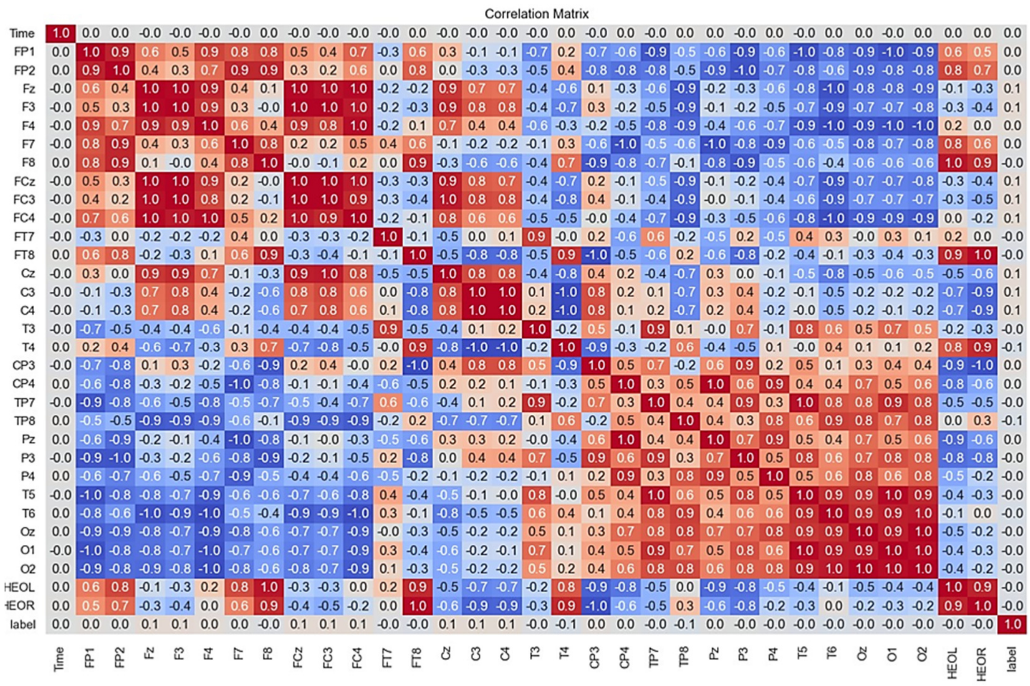

Fig. 5. EEG correlation matrix after MARA.

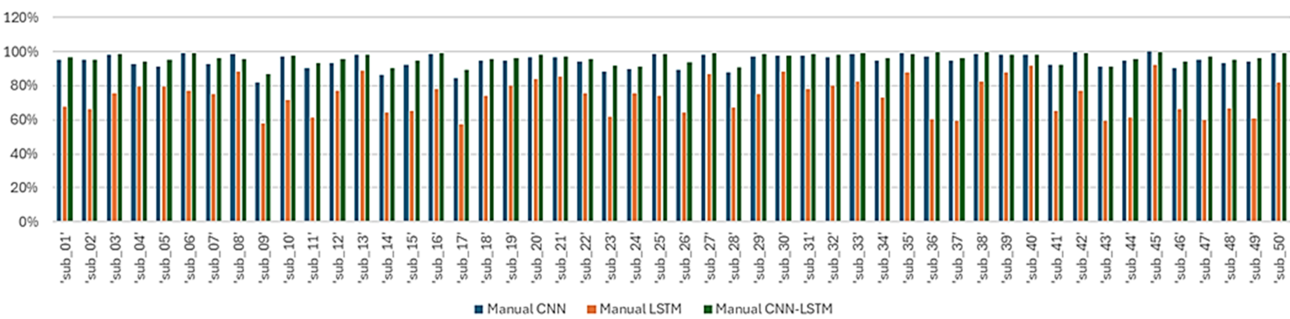

Fig. 6. Accuracy of the EMAR artifact removal technique.

For the CNN, the accuracy ranges in 51–90%, with some subjects (e.g., sub_06, sub_13, sub_21) showing very high scores. LSTM achieves 51–80%, generally lower than CNN, while CNN-LSTM reaches 51–91%. SASICA balances automation and specificity, targeting artifacts like eye movements. The accuracy of the CNN is very high (81–100%), with several subjects near perfect. LSTM achieves 55–91%, generally outperforming MARA. CNN-LSTM reaches 85–100%, showing strong improvements from SASICA's artifact removal. EMAR focuses on eye and muscle artifacts, with effectiveness depending on operator expertise. CNN accuracy ranges from 82–99%, consistently high across subjects. LSTM scores 57–92%, higher than MARA and similar to SASICA. CNN-LSTM ranges in 60–100% as shown in Figure 6, with many subjects performing well, highlighting the benefits of manually cleaned data.

IV. CONCLUSION

This study contributes to the area of EEG-based motor imagery prediction for stroke rehabilitation by combining sophisticated artifact removal techniques with a hybrid deep learning model, thus overcoming the shortcomings of existing methods. Conventional approaches often prove inadequate for dealing with EEG data contaminated with noise and artifacts, thereby impeding the progress of dependable BCI systems. This study addresses this disparity by using a fusion of CNN and LSTM models, which allows the use of both spatial and temporal characteristics of the EEG data, leading to a notable improvement in classification accuracy. The scientific rationale for this study is based on the strong preprocessing framework that improves the quality of EEG data by using techniques such as MARA, SASICA, and EMAR. Visually, MARA produces the smoothest overall signal, indicating comprehensive artifact removal, while SASICA shows noticeable improvement but retains some variability, suggesting partial artifact removal. EMAR effectively reduces specific artifacts, resulting in cleaner signals in affected segments, though not as uniformly smooth as MARA. Each artifact removal method has its strengths: MARA offers the most comprehensive cleaning but can homogenize the data too much, SASICA balances automation and specificity, and EMAR excels in targeting eye and muscle artifacts.

These methods effectively eliminate different types of artifacts, resulting in cleaner and more dependable EEG signals. The application of this preprocessing technique, in conjunction with the hybrid CNN-LSTM model, exhibits a greater capacity to categorize motor imagery tasks compared to separate models. SASICA particularly stands out for CNN and CNN-LSTM models, achieving near-perfect accuracy for many subjects. EMAR removal, while effective, depends on the operator's skill but generally provides excellent results for CNN and CNN-LSTM models. MARA, while comprehensive, shows more variability in performance, suggesting it might over-remove or miss certain artifacts, impacting the model's accuracy. SASICA stands out with high average accuracy, achieving 95% for CNN and 96% for CNN-LSTM, highlighting its effectiveness in artifact removal. Similarly, the EMAR method also delivers strong performance, with 95% for CNN and 96% for CNN-LSTM, though it relies on operator skill. MARA, while comprehensive, shows more variability, with a lower average accuracy of 67% for CNN and 69% for CNN-LSTM, suggesting it may over-remove or miss certain artifacts, impacting model performance.

This advancement lays the foundation for the development of more efficient BCI systems in stroke rehabilitation. Future research should prioritize the expansion of this approach to bigger and more varied datasets to confirm its applicability and investigate the incorporation of real-time feedback mechanisms in BCI applications to improve the effectiveness of rehabilitation interventions. Current research is examining the potential use of these methods in various neurological disorders and exploring the application of transfer learning to customize models for individual patient traits. This research aims to create personalized and adaptable tools for neurorehabilitation, ultimately leading to better patient outcomes.

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