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EEG-BASED MOTOR IMAGERY PREDICTION FOR STROKE REHABILITATION USING QUINE-MCCLUSKEY-LATENT ATTENTION NETWORK WITH DANDELION OPTIMIZER

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Abstract

Stroke is a leading neurological disorder caused by the rupture or blockage of cerebral blood vessels, leading to brain cell damage and impaired motor functions. Electroencephalography (EEG) Motor Imagery (MI) Prediction utilizes EEG a non-invasive technique with high temporal resolution to record brain activity during imagined movements. By analysing these motor imagery signals, predictive models can assist in monitoring and enhancing motor recovery, making EEG a promising tool in stroke rehabilitation. To address the need for accurate and interpretable MI prediction, the study presented an EEG-based motor imagery prediction framework using a Quine-McCluskey-Latent Attention Network integrated with Dandelion Optimizer (QMc-LAN-DaO). Initially, raw EEG signals are acquired from Brain-Computer Interface Competition IV-2a (BCI Competition IV-2a) dataset, undergo pre-processing using the Cubature Kalman Filter (CKF) for noise reduction, and are then normalized within [8-24 Hz] frequency band to preserve motor-related rhythms essential for motor imagery analysis. For feature extraction, the Clifford Fourier Mellin Transform (CFMT) is employed to obtain robust, scale- and rotation-invariant spatiotemporal features essential for distinguishing motor intentions. Then prediction using Quine-McCluskey Latent Attention Network (QMc-LAN) combines the strengths of Quine-McCluskey Binary Classifier (QMcBC), known for its logical feature minimization, with the Latent Attention Network (LAN), which captures task-relevant hidden representations. This hybrid approach enhances prediction accuracy by efficiently selecting and focusing on the most discriminative EEG features for motor imagery prediction. To further optimize performance, the Dandelion Optimizer (DaO) fine-tunes the loss function by adaptively balancing feature noise and repeatability error. The proposed QM-LAN with DaO delivers high accuracy of 99.94% and interpretability, making it a valuable tool for MI-based stroke rehabilitation, neurofeedback, and BCI applications.

Keywords— Motor Imagery Prediction, Stroke Rehabilitation, Electroencephalography, Cubature Kalman Filter, Clifford Fourier Mellin Transform.

I. INTRODUCTION

Stroke is a neurological condition caused by the occlusion or rupture of intracranial vessels, and damage to neuronal cells, with subsequent brain dysfunction. It is a significant source of worldwide mortality and chronic disability, and has a profound impact on the quality of life and independence of survivors [1]. Although advances in acute care have optimized survival rates, most patients still suffer from motor impairments, which interfere with daily activities and put a heavy burden on their families [2]. Neuroplasticity is the main driving mechanism of post-stroke recovery, allowing the brain to reorganize its neural connections. Facilitating neuroplasticity through successful rehabilitation is essential for motor recovery [3]. Recent years have seen the appearance of BCI systems as valuable tools in this area [4]. BCIs function as communication connectors between brain and external equipment, enabling the control of assistive devices by brain signals alone. This is especially useful for those with neuromuscular diseases like Amyotrophic Lateral Sclerosis, spinal cord injury, cerebral palsy, or stroke [5]. Of

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all the available BCI modalities, EEG has found widespread usage because of its non-invasiveness, low cost, and simplicity of use. EEG-based BCIs can process brain signals during MI a cognitive activity wherein people mentally rehearse movement without actual performance. MI activates the same neural circuits used for actual motor actions, and hence it is an effective tool for motor rehabilitation [6]. By decoding EEG signals during MI tasks, clinicians can determine patients' recovery progress and construct tailored rehabilitation programs. This not only accelerates healing process but also mitigates the burden on healthcare resources, making the healthcare model more sustainable. Additionally, the area has experienced exponential advancement with introduction of deep learning and domain adaptation methods. The techniques are designed to mitigate issues like the non-stationary character of EEG signals, which need to be calibrated often and lead to variability across sessions [7].

Stroke healing necessitates creative solutions because of chronic motor deficits that make daily tasks difficult and put a strain on caretakers. EEG-based BCIs, particularly those that use MI, present a viable non-invasive way to track and improve neuroplasticity driven rehabilitation. By combining deep learning and adaptive techniques, the accuracy of MI decoding is further increased, allowing for more individualized and long-lasting stroke treatment.

Contributions

The research's key contributions are listed below:

- **Data Collection:** EEG signals are collected from BCI Competition IV-2a dataset, enabling a standardized evaluation of MI prediction for stroke rehabilitation.
- **Pre-processing:** The raw EEG signals undergo noise reduction using Cubature Kalman Filter (CKF)**,** followed by normalization within the motor-related frequency band (8–24 Hz) to ensure consistent input quality.
- **Feature Extraction:** The Clifford Fourier Mellin Transform (CFMT) is employed to extract scale and rotation invariant spatiotemporal features from the pre-processed EEG signals, capturing essential patterns relevant to motor intention.
- **Classification:** MI prediction is performed using the proposed Quine-McCluskey-Latent Attention Network (QMc-LAN)**,** which:

  a.First applies Quine-McCluskey Binary Classifier (QcMBC) for interpretable logic-based decision-making, simplifying EEG feature patterns into minimal logical expressions for efficient MI prediction.

  b.Then refines prediction through the Latent Attention Network (LAN)**,** which emphasizes discriminative EEG regions using attention mechanisms.

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- **Optimization:** A Dandelion Optimizer (DaO) is integrated to fine-tune the training process by adaptively minimizing the loss, balancing noise sensitivity and feature repeatability to enhance prediction accuracy and robustness.

The paper is structured as follows: Section 1 contains introduction; Section 2 contains literature review; Section 3 contains methodology; Section 4 contains results; and Section 5 concludes the study.

II. LITERATURE SURVEY

Below is a summary of recent studies on EEG-based MI prediction.

In 2024, Ma, Z.Z. et.al [8] presented a novel two-phase multitask auto encoder (2PMTAE) framework was proposed to address class imbalance and ensure stable training of MTAE. The framework consisted of two phases: the generation of a class-specific target signal and the calculation of reconstruction loss based on the generated target signals, effectively aligning the objectives of the two loss functions. In subject-independent experiments, the proposed method significantly outperformed state-of-the-art techniques, achieving accuracies on the BCI Competition IV-2a and OpenBMI datasets, respectively.

In 2024, Ma, Z.Z. et.al [9] introduced a deep learning methodology was introduced to systematically evaluate three models convolutional neural networks (CNNs), Bidirectional Long Short-Term Memory (BiLSTM), and Recurrent Neural Network (RNN) to identify optimal approach for MI signal classification. Using BCI Competition IV-2a dataset, pre-processing step was applied.

In 2022, Altuwaijri, et.al [10] introduced a multibank CNN model was proposed in order to efficiently extract temporal and spatial information from unprocessed EEG data, with each branch corresponding to a different filter kernel size. The method's performance was validated using experimental results on two public datasets: the BCI Competition IV-2a and High Gamma Dataset.

In 2023, Lionakis, et.al [11] presented recent advances in computational power enabled deep learning algorithms to serve as robust tools for leveraging BCIs. A comprehensive review was conducted on deep and hybrid deep learning techniques used in MI-based BCI systems. The study explored the use of CNN auto encoders, and recurrent structures such as long short-term memory (LSTM) networks, referencing BCI Competition IV-2a dataset.

A. Problem statement

In BCI systems, MI based EEG classification poses challenges due to factors such as class imbalance, low signal-to-noise ratio, and subject variability. This affects development of accurate and generalizable models, especially in subject-independent framework. Traditional approaches are incapable of effectively extracting spatial-temporal features or adapting across users. Recent deep learning technologies, such as CNNs, RNNs, BiLSTM, and auto encoders, have been promising but have not yet been integrated into a unified, efficient, and robust framework for MI signal decoding across various datasets.

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III. PROPOSED METHODOLOGY

The suggested EEG motor imagery prediction model starts with data gathering from BCI Competition IV-2a dataset. The gathered EEG signals are pre-processed by Cubature Kalman Filter (CKF) and then normalized in the motor-related frequency band (8–24 Hz). Subsequently, Clifford Fourier Mellin Transform (CFMT) is utilized to extract robust spatiotemporal features. The classification is then performed by Quine-McCluskey-Latent Attention Network (QMc-LAN), the integration of QMBC for logical decision and LAN for attention-based refinement. Last but not least, Dandelion Optimizer (DaO) adjusts network parameters to reduce loss and improve prediction accuracy. The proposed method's block diagram is shown in Figure 1.

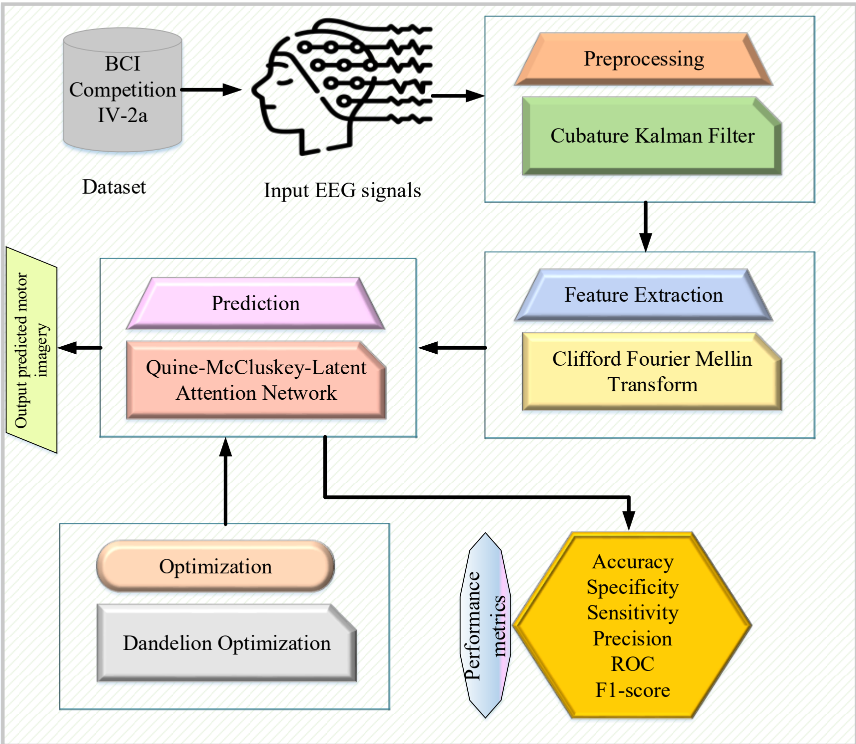

Fig.1. Proposed Methodology QMc-LAN-DaO's block diagram.

A. Dataset description

The BCI Competition IV-2a dataset consists of 5,184 trials in two sessions measured from nine participants for four MI tasks, left hand, right hand, foot, and tongue [12]. At each trial consisting of 2 s of screen viewing, 4 s of MI, and 1.25 s of rest time, EEG data were recorded at a sampling rate of 250 Hz from 22 channels. The collected EEG data are fed for pre-processing.

B. Cubature Kalman Filter (CKF) for pre-processing

Cubature Kalman Filter (CKF) plays a vital role in pre-processing of EEG signals for MI prediction by removing noise and artifacts while preserving the essential structural and

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frequency-specific information necessary for accurate prediction [13]. Although raw EEG data is directly used as input, CKF enhances signal fidelity within the critical [8-24 Hz] frequency band, bypassing extensive manual feature engineering and enabling efficient learning by deep learning models. CKF improves EEG data by stabilizing signal amplitude, reducing power-line interference, and ensuring smooth transitions across temporal sequences, which is especially beneficial in clinical settings such as stroke rehabilitation. To model EEG signal evolution as a stochastic dynamic system, CKF employs a State Space Model (SSM), described mathematically as follows in Equation (1) and (2),

$$c_i = a(c_{i-1}) + d_{i-1} \quad (1).$$

$$w_i = s(c_i) + v_i \quad (2).$$

where, c_i represents the time interval i at every time, $a(c_{i-1})$ represents state transition function, d_{i-1} represents the noise generated at each step of the process $i-1$, w_i is the measurement made at each time period i, $s(c_i)$ represents the measurement function of the state mapping c_i and v_i represents the noise of measurement at time i. Provided the sigma points in Equation (3) and (4),

$$\chi_{m,i-1} = \bar{c}_{i-1|i-1} + \sqrt{gH_{i-1|i-1}}[1]_m \quad (3).$$

$$\chi_{m,i} = \bar{c}_{i|i-1} + \sqrt{gH_{i|i-1}}[1]_m \quad (4).$$

where $\chi_{m,i-1}$ denotes the current status estimation at time $i-1$, $\bar{c}_{i-1|i-1}$ represents the earlier state of estimation at time $i-1$, $H_{i-1|i-1}$ denotes error covariance matrix, $[1]_m$ indicates the unit vector for m^{th} iteration, $\bar{c}_{i|i-1}$ is now the prior state estimate, $H_{i|i-1}$ represents the covariance matrix at time i. CKF improves feature clarity in EEG motor imagery by normalizing. This preprocessing approach using CKF preserves essential EEG signal characteristics and feeds the data into feature extraction stage for accurate MI prediction.

C. Clifford Fourier Mellin Transform (CFMT) for feature extraction

To ensure robust prediction of motor imagery EEG signals for stroke rehabilitation, it is critical to extract features that remain invariant to non-stationary variations such as shifts in scale, temporal distortions, and inter-subject variability. These challenges are analogous to geometric transformations in image data. Therefore, the Clifford Fourier Mellin Transform (CFMT) is used as a powerful method for transformation invariant feature extraction in EEG signal space [14]. The preprocessed and normalized signals are fed into CFMT. Each branch employs distinct convolutional kernel sizes to capture multi-scale spatio-temporal dependencies across EEG channels. These act on the CFMT transformed signal space,

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effectively encoding rich, class-discriminative patterns necessary for accurate MI prediction. The CFMT expression is given in Equation (5),

$$SD_{g,A}(h,u)=\int_0^{\infty}\int_0^{2\pi} s^{-ju} e^{\frac{1}{2}h\chi(A+P_4A)} g(s,\chi) e^{\frac{1}{2}h\chi(A+P_4A)} \frac{ds}{s} d\chi \quad (5).$$

where h is a constant, $SD_{g,A}(h,u)$ is the scale-dependent transform, χ denotes angular parameter, $P_{2,4}$ represents a Clifford algebra operator, $g(s,\chi)$ indicates the input signal, $e^{\frac{1}{2}h\chi(A+P_4A)}$ is the term for exponential weighting, $\frac{ds}{s}, d\chi$ is the integration over scale. Further simplification is given in Equation (6) and (7),

$$\|SD_{f\vartheta,A}(h,u)\| = \|SD_{g\vartheta,A}(h,u)\| \quad (6).$$

$$\|SD_{f\vartheta,A}(h,u)\| = \left(\frac{1}{\vartheta}\right)^{\vartheta} \|SD_{g\vartheta,A}(h,u)\| \quad (7).$$

where ϑ represents a constant, $SD_{fg,A}(h,u)$ denotes the scaled version of signal decomposition. After applying CFMT, the transformed signal retains high-fidelity representations of EEG motor imagery dynamics, which are then fed into QMc-LAN, to enhance the robustness and generalization of EEG-based prediction.

D. Prediction of EEG motor imagery by Quine-McCluskey-Latent Attention Network (QMc-LAN)

After feature extraction, the extracted representations are passed through Quine-McCluskey-Latent Attention Network (QMc-LAN). To accomplish accurate and interpretable prediction of motor imagery EEG signals for stroke rehabilitation, QMc-LAN is used. This hybrid model combines (QMcBC) logic-based decision-making with (LAN) attention-driven learning, ensuring robust predictions while emphasizing neurologically relevant EEG features.

a. Quine-McCluskey Binary Classifier (QMcBC)

The QMcBC acts as the initial predictor by applying a Boolean logic-based strategy derived from the Quine-McCluskey minimization method, offering interpretable decisions crucial in medical and neurorehabilitation contexts [15]. By fusing outputs from multiple base predictors, it ensures high diagnostic precision and robust prediction of different MI classes (left or right hand, foot, and tongue imagery). The simplified Boolean expressions help in understanding the basis of each prediction, aiding clinicians in decision validation. The worst-case total comparisons during logic minimization is given by Equation (8),

$$A = \sum T_j^m \cdot T_{j+1}^m \quad (8).$$

where m denotes number of variables, $j = 0,1,2,\ldots(m-1)$. The total comparisons A' is given by Equation (9),

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$$A' = m.2^{m-1} \qquad (9).$$

where A' represents total no. of comparisons. Thus, by QMcBC, prediction is initially performed, and for further refinement, the LAN enhances class-specific feature focus.

b. Latent Attention Network (LAN)

Following QcMBC, Latent Attention Network (LAN) refines the decision-making process by learning attention masks over the input EEG features, focusing on class-discriminative and spatially/temporally salient regions of the brain signals [16]. The LAN identifies which EEG channels or time segments contribute most to the motor intention (left-hand imagery), improving boundary separation and prediction confidence. LAN defines a function that generates an attention mask $R(y)$, highlighting important parts of the input y. This mask indicates which components of y are crucial for the network $B(y)$'s prediction. It also helps identify how much noise each input part can tolerate without significantly changing the output. The two additional design components to formulate this notation is given in Equation (10),

$$\begin{aligned} &J_B : L^k \times L^l \mapsto L \\ &M : L^e \mapsto L \end{aligned} \qquad (10).$$

where J_B is the loss function in output space B, M denotes the noise probability density. The noisy factor δ is as follows in Equation (11),

$$\hat{y} = R(y) \cdot \delta + (1 - R(y)) \cdot y \qquad (11).$$

where 1 represents tensor of ones, $\hat{y}$ indicates the modified version of input y, $R(y)$ is a softmask function. Therefore, for each input y, minimize the following training goal in order to train the LAN R as by Equation (12),

$$J_{LAN}(y) = f_{\mu \sim M}\left[J_B(B(\hat{y}), B(y)) - \alpha \overline{R(y)}\right] \qquad (12).$$

where $\overline{R(y)}$ represents the attention mask's mean value for a certain input, $\alpha > 0$ is a hyperparameter that weighs the degree of input corruption against the repeatability error in relation to J_B, $f_{\mu \sim M}[\cdot]$ denotes averaging function over M, $B(\cdot)$ indicates mapping function. The proposed QMc-LAN integrates logical interpretability QcMBC with attention refinement LAN for accurate and explainable EEG prediction of MI. It enhances stroke rehabilitation by identifying critical EEG regions for neurofeedback and BCI guidance. Then, DaO fine-tunes the loss function J_B by improving overall prediction accuracy.

E. Fine-tuning loss function by Dandelion Optimizer

The predicted motor imagery class are fed into Dandelion Optimizer (DaO) for minimizing loss functions. DaO is inspired by the natural dispersal mechanism of dandelion seeds carried

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by wind over long distances [17]. It mimics three key phases: ascent and descent, representing exploration and exploitation in the search space. This biologically inspired strategy enables diverse, adaptive search behaviour for global optimization. The DaO is used for optimizing the loss functions of QcMBC-LAN.

Step 1: Initialization

A population of candidate solutions, representing feature selection vectors, is initialized to begin the optimization process. The DaO population can be expressed as the following matrix in Equation (13),

$$population = \begin{bmatrix} y_1^1 & \cdots & y_1^{\dim} \\ \vdots & \ddots & \vdots \\ y_A^1 & \cdots & y_A^{\dim} \end{bmatrix} \quad (13).$$

where y_i^i represents the j^{th} variable for i^{th} candidate solution, $A, \dim$ represents number of seeds in swarm, andnumber of variables in problem. In initial phase the candidatepositions are randomly selected by Equation (14),

$$y_j = ty + rand \times (as - ty) \quad (14).$$

where ty and as are the lower and upper bonds respectively, $rand$ denotes the random number.

Step 2: Random Generation

Within predetermined parameters, initial seeds which stand in for potential solutions are dispersed at random throughout the search space.

Step 3: Fitness Function

The fitness functions can accomplish the objective function, which is to predict the motor imagery. Equation (15) represents the fitness function,

$$FF = Min[J_B] + Max[acc] \quad (15).$$

where $Min[J_B]$ denotes minimization of loss function J_B and $Max[acc]$ denotes maximization of accuracy.

Step 4: Exploration (Ascent phase)

The DaO mimics dandelion seeds spiraling upward in the wind to explore the search space efficiently using Equation (16),

$$y_{s+1} = y_s + \delta \times h_y \times h_x \times \ln X \times (y_s - y_r) \quad (16).$$

where X denotes the speed of the wind, δ is a nonlinear adaptive parameter, h_y and h_x are the motion parameters from wind model, y_r represents the randomly selected position.

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Step 5: Exploitation (Descent phase)

Seeds descend using Brownian motion, refining their positions around the population mean for improved exploitation. It is given in Equation (17),

$$y_{s+1} = y_s - \delta \times \gamma_s \times (y_{mean} - \delta \times \gamma \times y_s) \quad (17).$$

where y_{mean} denotes the mean of the current population, γ_s adjusts descent based on Brownian motion.

Step 6: Termination

The optimization process using DaO halts upon reaching the maximum number of iterations, the change in loss becomes negligible, or the target loss threshold is achieved. These conditions ensure convergence while avoiding unnecessary computations. Thus by DaO the network is fine-tuned by minimizing loss.

IV. RESULT

The QcMBC-LAN-DaO method's performance in motor imagery prediction is highlighted in this section along with its evaluation and results. Python is used for both implementation and analysis.

A. Performance Analysis of Proposed Model

The BCI Competition IV-2a dataset is used to evaluate the effectiveness of proposed model, with an emphasis on important assessment criteria. The model's performance is thoroughly evaluated by analysing its sensitivity, accuracy, F1-score, precision, specificity, and Receiver Operating Characteristic (ROC) curve. These metrics show how well the model can predict motor imagery, how well it can converge during training, and how well it can differentiate between different EEG data classes.

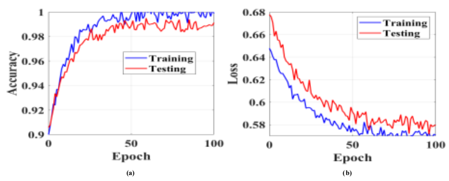

Fig.2. (a) Accuracy and (b) Loss vs. Epoch.

The figure 2(a) shows training and testing accuracy across 100 epochs. Both trendlines have a consistent rise, with training accuracy up to almost 1.0 and testing accuracy tending to 0.985, showing robust generalization and successful learning. The figure 2(b) shows the training and testing loss patterns. Both losses come down steadily, with the training loss being a trifle lower than testing. This shows model convergence with little overfitting, guaranteeing high performance on new data.

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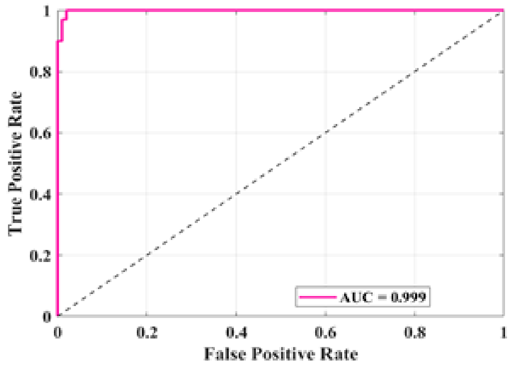

Fig.3. ROC Curve analysis of BCI Competition IV-2a dataset

Figure 3 shows that ROC curve provides a visual representation of classifying ability of the developed model with BCI Competition IV-2a dataset. A steep incline towards the top-left shows high classifying capacity, with less false positive and more true positive. The model attains a very high Area Under the Curve (AUC) measure of 0.999, which reflects nearly perfect discriminant capability. This excellent AUC validates the model's strength in classifying motor imagery tasks with high sensitivity, specificity, and reliability in separating multiple EEG signal classes under different conditions.

B. Comparative analysis

The Accuracy, Sensitivity, Specificity, F1-score, and ROC are key metrics used to evaluate the performance of proposed architecture for motor imagery classification. Existing methods such as 2PMTAE [8], BiLSTM [9], CNN [10], and LSTM [11] are compared using the BCI Competition IV-2a dataset. Table 1 presents comparative analysis of these methods, highlighting their prediction effectiveness and superiority of proposed approach in handling EEG signal patterns for reliable brain-computer interface performance.

TABLE I. PERFORMANCE COMPARISON OF BCI COMPETITION IV-2A DATASET

Methods	Accuracy (%)	Sensitivity (%)	F1-Score (%)	Specificity (%)	Precision (%)
2PMTAE [8]	86	81	86	79	81
BiLSTM [9]	82	76	75	80	78
CNN [10]	83	88	83	76	84
LSTM [11]	87	73	81	84	87
QMc-LAN-DaO (proposed)	**99.94**	**99.63**	**99.52**	**99.78**	**99.59**

Table 1 shows the comparison of performances of various state-of-the-art techniques 2PMTAE, BiLSTM, CNN, and LSTM on the BCI Competition IV-2a dataset based on key

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metrics: Accuracy, Sensitivity, F1-Score, Precision and Specificity. Among all, the presented model with remarkable Accuracy of 99.94%, Sensitivity of 99.63%, F1-Score of 99.52%, Precision of 99.59% and Specificity of 99.78% outperforms others significantly. The remaining models exhibit moderate performance with Accuracy ranging from 82% to 87%. This reflects the improved higher classification performance and robustness of the proposed method in EEG-based motor imagery tasks.

V. CONCLUSION

This research proposed a strong and interpretable model for EEG MI prediction optimized for stroke rehabilitation use. First, EEG signals are recorded from the BCI Competition IV-2a dataset, offering well-annotated multi-channel MI data. The signals are pre-processed with CKF in order to effectively filter out noise and artifacts while retaining signal dynamics. The pre-processed signals are normalized in the motor-related frequency band (8-24 Hz). CFMT is then used to obtain rotation- and scale-invariant spatiotemporal features. The prediction stage utilizes QMc-LAN, which integrates logical rule-based decision making through QMcBC and sophisticated attention-based learning with LAN. This hybrid architecture improves interpretability and prediction performance. Then, DaO is utilized to reduce training loss through fine-tuning model parameters to improve generalization. Overall, the proposed methodology presents an effective, explainable solution for MI-based stroke rehabilitation systems.

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