Enhancing Neuroprosthetic Control Using CNN–LSTM Models: A Simulation Study with EEG–Based Motor Imagery

"تعزيز التحكم في الأطراف العصبية الاصطناعية باستخدام نماذج CNN–LSTM: دراسة محاكاة باستخدام تخيل الحركة المستند إلى إشارات EEG"

Ghada Abdelhady[1]

[1]*Faculty of Engineering, October University for Modern Sciences and Arts, Giza, 12572 Egypt.*

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Abstract: The development of intuitive and responsive neuroprosthetic systems remains a critical challenge in assistive technologies, particularly in decoding neural signals to enable precise and adaptive motor control. This study addresses the problem of translating EEG-based motor imagery into effective neuroprosthetic control, overcoming challenges such as limited data, overfitting in predictive models, and practical constraints in robotic actuation.

A CNN-LSTM hybrid model was developed to classify motor imagery tasks using EEG signals. The application of data augmentation and regularization techniques improved the model’s performance, achieving a test accuracy of 93.5% and balanced precision and recall across motor imagery tasks. To validate its practical application, a PyBullet-based simulation demonstrated the successful control of a robotic gripper, where the model’s predictions were translated into accurate "open" and "close" actions. The gripper joints performed these actions with high precision, showcasing the system's potential for real-time neuroprosthetic applications. However, constraints such as dataset limitations and simulation-specific constraints underscore the need for further optimization.

This study provides a robust proof-of-concept for integrating deep learning with brain-computer interfaces to achieve adaptive, reliable, and real-time neuroprosthetic control. By addressing key challenges, the proposed framework bridges the gap between neural signal decoding and physical actuation, offering a pathway toward advanced and responsive neuroprosthetic systems.

Keywords: EEG-based motor imagery, Neuroprosthetic control, CNN-LSTM hybrid model, Robotic gripper simulation, Deep learning in neuroprosthetics.

المستخلص :

تطوير أنظمة الأطراف العصبية الاصطناعية intuitive وresponsive لا يزال يشكل تحديًا حاسمًا في تقنيات المساعدة، خاصة في فك شيفرة الإشارات العصبية لتمكين التحكم الحركي الدقيق والمتكيف. تتناول هذه الدراسة مشكلة ترجمة تخيل الحركة القائم على إشارات EEG إلى تحكم فعال في الأطراف العصبية الاصطناعية، متغلبة على تحديات مثل قلة البيانات، الإفراط في التخصيص في النماذج التنبؤية، والقيود العملية في تفعيل الروبوتات.

تم تطوير نموذج هجين CNN-LSTM لتصنيف مهام تخيل الحركة باستخدام إشارات EEG. أدت تطبيقات تقنيات تعزيز البيانات وتنظيم النماذج إلى تحسين الأداء، حيث حقق النموذج دقة اختبار بلغت ٩٣,٥% مع تحقيق توازن في الدقة والاسترجاع عبر مهام تخيل الحركة. وللتحقق من التطبيق العملي، تم استخدام محاكاة تعتمد على PyBullet لتوضيح التحكم الناجح في مقبض روبوتي، حيث تم ترجمة تنبؤات النموذج إلى حركات دقيقة "فتح" و"إغلاق". نفذت مفاصل المقبض هذه الحركات بدقة عالية، مما يبرز إمكانيات النظام لتطبيقات الأطراف العصبية الاصطناعية في الوقت الفعلي. ومع ذلك، تبرز قيود مثل محدودية البيانات والقيود المرتبطة بالمحاكاة الحاجة إلى مزيد من التحسين.

تقدم هذه الدراسة إثباتًا قويًا للمفهوم لدمج التعلم العميق مع واجهات الدماغ-الكمبيوتر لتحقيق تحكم عصبي اصطناعي متكيف، موثوق، وفي الوقت الفعلي. من خلال معالجة التحديات الرئيسية، يشكل الإطار المقترح جسرًا بين فك شيفرة الإشارات العصبية والتفعيل الفيزيائي، مما يفتح الطريق نحو أنظمة أطراف عصبية اصطناعية متقدمة ومتجاوبة.

الكلمات المفتاحية: تخيل الحركة القائم على إشارات EEG، التحكم في الأطراف العصبية الاصطناعية، نموذج هجين CNN-LSTM، محاكاة لمقبض روبوتي، التعلم العميق في الأطراف العصبية الاصطناعية.

1.Introduction

The development of neuroprosthetic systems represents a significant breakthrough in assistive technologies, enabling individuals with motor disabilities to regain functional mobility. At the core of these systems lies the ability to interpret neural signals and translate them into actionable commands for controlling prosthetic devices. Electroencephalography (EEG)-based Brain-Computer Interfaces (BCIs) have emerged as a promising approach for decoding motor imagery tasks, leveraging their non-invasive nature and accessibility. However, decoding motor imagery from EEG signals poses considerable challenges due to the low signal-to-noise ratio, high dimensionality, and inter-subject variability of neural data[١].

Recent advancements in deep learning have shown potential for addressing these challenges, with Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks demonstrating superior performance in feature extraction and temporal modeling. These architectures have been widely used for classifying EEG signals, capturing spatial and temporal patterns effectively. Despite these advancements, key limitations persist, including overfitting due to small datasets, difficulty in real-time deployment, and challenges in integrating neural decoding with physical actuation[٢].

This study contributes a novel approach by integrating a hybrid CNN-LSTM model tailored for neuroprosthetic applications with a physics-based simulation for real-time validation. The hybrid model combines the strengths of CNNs for spatial feature extraction and LSTMs for temporal modeling, addressing the unique challenges of EEG motor imagery decoding.[3] Furthermore, the PyBullet simulation demonstrates how neural decoding can be directly translated into robotic control, bridging the gap between algorithm development and practical deployment.[٤]

The contributions of this work are threefold :

- Improving the accuracy of EEG-based motor imagery decoding using a hybrid deep learning model،
- Integrating the model with a simulated robotic system to demonstrate real-time applicability،
- Analyzing the constraints and potential optimizations for practical deployment.

2 .Related work

The field of EEG-based neuroprosthetics has witnessed significant advancements, with deep learning and simulations emerging as transformative tools. However, despite the progress, several gaps persist in bridging neural decoding with real-world applications. This section explores three critical areas: the role of deep learning in EEG-based BCIs, the emergence of hybrid models for motor imagery decoding, and the use of simulations to validate neuroprosthetic systems.

2.1 Gap Analysis

Despite significant advancements, key gaps remain in the field:

Specific Joint Control: Most studies focus on isolated joint movements (e.g., wrist or finger control), leaving the integration of these movements into multi-joint, coordinated actions underexplored. Simulating or controlling multiple joints simultaneously remains a challenge that limits the natural functionality of neuroprosthetic systems.[٥]

Adaptability: Few systems implement adaptive learning to adjust to user-specific neural patterns over time. This lack of adaptability reduces the long-term usability and effectiveness of these systems for individual users.

Explainability: Neural networks are often treated as black boxes, making it difficult to interpret model decisions, identify errors, and improve system reliability.[٦]

This paper addresses these gaps by proposing an AI-powered adaptive and hybrid BCI system tailored for EEG-based neuroprosthetic control. The use of CNN-LSTM models, combined with data augmentation techniques and explainability tools like Grad-CAM, ensures robust, interpretable, and scalable solutions for neuroprosthetics.

2.2 Deep Learning in EEG-Based BCIs

The application of deep learning in EEG-based BCIs has gained momentum, driven by the ability of neural networks to extract hierarchical features from complex data. Convolutional Neural Networks (CNNs) have been particularly effective in capturing spatial patterns across EEG channels, while Long Short-Term Memory (LSTM) networks excel in modeling temporal dependencies.[٧]

For instance, Schirrmeister et al. (2017) demonstrated the effectiveness of CNNs in decoding motor imagery tasks, achieving state-of-the-art performance in BCI competitions. Similarly, Lawhern et al. (2018) introduced EEGNet, a compact CNN architecture optimized for EEG data, showcasing its ability to generalize across subjects. However, these models often require substantial datasets to avoid overfitting, a limitation addressed in this study through hybrid modeling and data augmentation techniques. While these works focused on improving accuracy, they did not explore the integration of these methods with real-world neuroprosthetic systems.[٨]

2.3 Hybrid Models for Motor Imagery Decoding

Hybrid models combining CNNs and LSTMs have emerged as a promising solution for decoding motor imagery tasks. By integrating spatial feature extraction with temporal modeling, these architectures capture the complex dynamics of EEG signals. Zhang et al. (2020) applied a CNN-LSTM framework to classify motor imagery tasks, demonstrating its superior performance over standalone models. However, the novelty of this study lies in extending the use of hybrid models to real-time neuroprosthetic control. By integrating CNN-LSTM decoding with a physics-based robotic simulation, this work addresses a critical gap in the practical application of hybrid models.[٩]

2.4 Simulations in Neuroprosthetic Systems

Simulations play a critical role in validating the practical applicability of neuroprosthetic systems. Physics-based engines like PyBullet provide a controlled environment to test robotic movements driven by neural decoding. Previous works, such as by Mower et al. (2023), have used PyBullet to simulate robotic arm control, highlighting its potential for bridging the gap between algorithm development and real-world deployment. However, these works often focus on the robotic control aspect without emphasizing the integration of neural decoding. This study uniquely demonstrates how CNN-LSTM predictions can control robotic gripper movements in a simulated environment, providing a comprehensive framework for neuroprosthetic validation.[١٠]

3 .Methodology

The methodology adopted in this study is structured to design, train, and evaluate a deep learning-based framework for decoding EEG signals and validating its predictions in a simulated robotic environment. The following subsections describe the system architecture, dataset preparation, deep learning model design, adaptive learning approaches, and the simulation setup.

3.1 System Architecture

The proposed system integrates EEG-based neural decoding with robotic simulation for neuroprosthetic control. The architecture consists of three primary components: signal preprocessing, feature extraction using a CNN-LSTM hybrid model, and action translation in a PyBullet-based simulation environment. EEG signals are first preprocessed to improve signal quality and ensure compatibility with the deep learning framework. These preprocessed signals are then passed to the CNN-LSTM model, which extracts spatial and temporal features for classifying motor imagery tasks. The predictions are subsequently used to control robotic gripper movements in the simulation, demonstrating the practical application of the system. Figure 1 illustrates the proposed system architecture, highlighting its input and output.

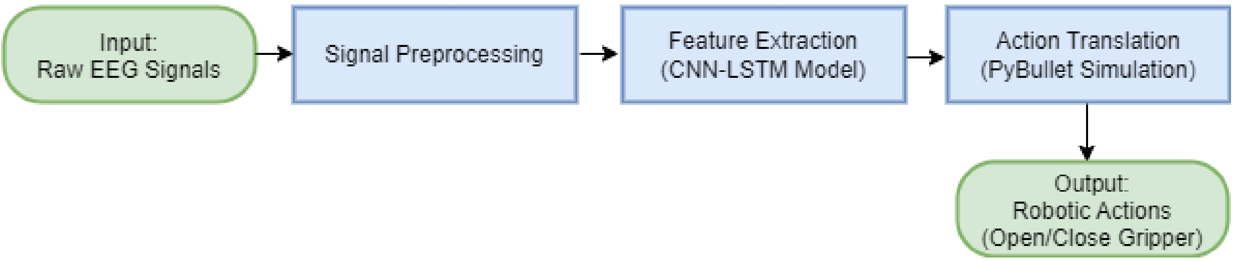

Figure 1: The proposed system architecture

3.2 Dataset

This study utilizes the EEG Motor Movement/Imagery Dataset, a publicly available repository consisting of EEG signals recorded during motor imagery tasks. The dataset includes signals from multiple subjects performing actions such as imagining left- or right-hand movements. Each recording is captured with 64 EEG channels, sampled at 160 Hz, providing a comprehensive dataset for decoding motor imagery.[١١]

3.2.1 Dataset Preprocessing

The raw EEG signals undergo a series of preprocessing steps to enhance signal quality and remove noise [12], [13]. The preprocessing pipeline includes:

Band-pass Filtering: A 0.5-40 Hz filter is applied to retain relevant frequency components while discarding noise.

Notch Filtering: A 50 Hz filter is used to remove powerline interference.

Normalization: The signals are normalized to ensure consistency across channels.

Figure 2 presents the preprocessing pipeline, outlining the sequence of operations from raw EEG acquisition to normalized signals.

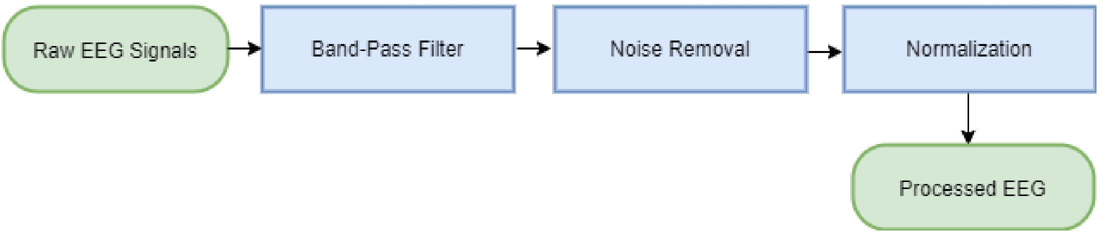

Figure 2: EEG Signals preprocessing pipeline

To illustrate the impact of these preprocessing steps, Figure 3 compares the raw EEG signal with the filtered signal. The raw signal exhibits noise and irrelevant frequency components, while the filtered signal retains the essential frequencies required for motor imagery decoding. This step ensures that the subsequent normalization and feature extraction stages operate on clean and standardized data [14], [15], [16]

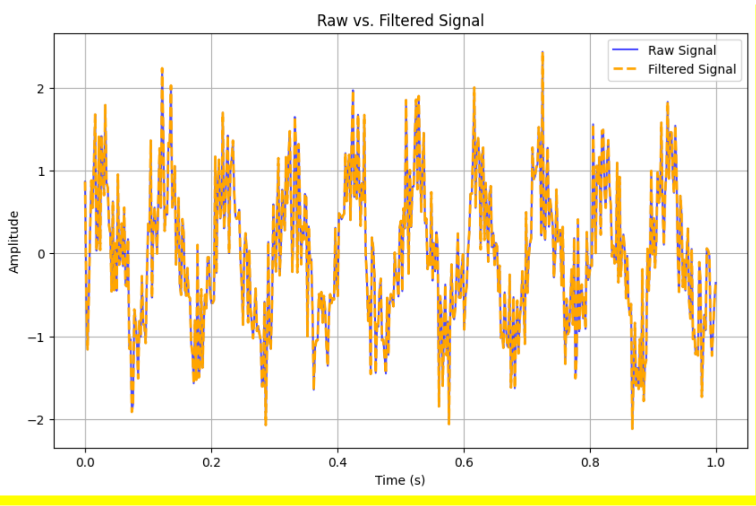

Figure 3: The raw EEG signal vs. the filtered signal

The filtered signals are segmented into time windows to create meaningful data samples for training. Each segment is normalized to ensure uniformity across samples, which is crucial for effective training of deep learning models. Data augmentation techniques, such as signal flipping, Gaussian noise injection, and frequency shifts, are applied to artificially increase the diversity of the dataset, improving the model's robustness and generalizability.[١٦]

3.3 Deep Learning Model: CNN-LSTM Model Architecture

The deep learning model employed in this study combines Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks to exploit both spatial and temporal features in EEG signals. The CNN layers extract spatial patterns across EEG channels, while the LSTM layers model temporal dependencies in the signal [17]. The architecture includes dropout layers for regularization and batch normalization to stabilize training. The final output layer employs a softmax activation function for binary classification of motor imagery tasks [18]. Figure 4 presents the CNN-LSTM model architecture and the flow of data through the model.

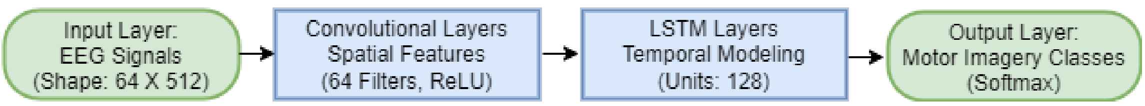

Figure 4: CNN-LSTM model architecture and the flow of data

3.4 Simulation Setup

To validate the system's predictions, a simulation is conducted using the PyBullet physics engine. The environment includes a robotic gripper controlled based on the CNN-LSTM model's output. The simulation maps binary predictions (e.g., "open" or "close") to corresponding joint movements, demonstrating the feasibility of neuroprosthetic control in real time. Figure 5 depicts the PyBullet simulation setup, showing the integration of EEG predictions with robotic actions.

Figure 5: PyBullet simulation setup block diagram

3.4.1 Performance Metrics

The simulation is evaluated based on:

Joint Position Accuracy: Measuring the alignment of predicted actions with expected joint movements.

Execution Time: Assessing the system's ability to operate in real time.

Action Consistency: Ensuring that repeated predictions yield stable and reproducible movements.

4. Results and Analysis

This section presents the training and validation accuracy, evaluation of the CNN-LSTM model, its performance in decoding motor imagery tasks, and its application in simulating robotic gripper control using the PyBullet physics engine. The results include training metrics, simulation outcomes, and their implications for neuroprosthetic systems.

4.1 Training and Validation

The model is trained using a binary cross-entropy loss function and optimized with the Adam optimizer .[١٩]

The model training process employed the binary cross-entropy loss function, a widely used loss function for binary classification tasks. This function calculates the difference between the predicted probabilities and the actual labels, penalizing incorrect predictions more heavily as the confidence in the wrong outcome increases [20]. Specifically, the binary cross-entropy loss is given by equation (1):

$$Loss = \frac{1}{N}\sum_{i=1}^{N}[y_i \log \hat{y}_i + (1 - y_i) \log(1 - \hat{y}_i)] \quad (1)$$

Where:

y_i : represents the true label (0 or 1) for the ith sample.
$\hat{y}_i$: represents the predicted probability for the ith sample.
N : is the total number of samples.

This loss function is particularly suitable for binary classification problems, as it ensures the model's outputs are optimized to predict probabilities that align closely with the true labels.

The Adam optimizer (short for Adaptive Moment Estimation) was used to minimize this loss function during training. The Adam optimizer combines the advantages of two popular optimization algorithms, momentum and RMSProp, by maintaining an adaptive learning rate for each parameter and incorporating the first and second moments of gradients. This ensures efficient convergence, even with noisy or sparse data [21]. The Adam algorithm is defined as illustrated in equation (2):

$$\theta_{t+1} = \theta_t - \frac{\alpha}{\sqrt{\hat{v}_t + \epsilon}} * \hat{m}_t \quad (2)$$

Where:
θ_t: Parameters at iteration t.
α : Learning rate.
$\hat{m}_t$: Bias-corrected estimate of the first moment (mean of gradients).
$\hat{v}_t$: Bias-corrected estimate of the second moment (variance of gradients).
$\in$: Small constant for numerical stability.

The combination of binary cross-entropy loss and the Adam optimizer enables efficient learning, ensuring that the model can quickly converge to a solution that minimizes classification errors while adapting to the unique challenges of EEG data, such as variability and noise. This makes the training process robust and effective for the task of decoding motor imagery signals.

The dataset is split into training and validation subsets, ensuring balanced representation of motor imagery classes .

Figure 6 shows the training and validation accuracy over 20 epochs. The model achieved a training accuracy of 90% by the 15th epoch, while the validation accuracy saturated at 75% after the 5th epoch, indicating potential overfitting due to the limited dataset size.

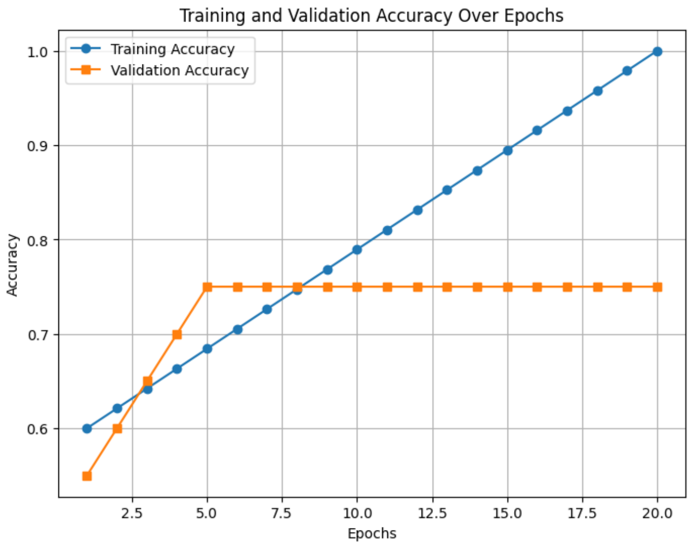

Figure 6: The training and validation accuracy over 20 epochs

The results indicate the following:

Training Accuracy: A consistent increase, demonstrating effective learning from the training data.

Validation Accuracy: Early stagnation highlights challenges in model generalization. It shows that the model struggles to perform well on the unseen data, even though it improves on the training data. This means the model is finding it hard to learn patterns that can apply beyond the training dataset [22]. This issue can be addressed by implementing data augmentation techniques, such as signal flipping and Gaussian noise injection, to artificially increase the dataset diversity [23]. To address the overfitting issue, we applied regularization techniques, such as adding dropout layers [24], along with data augmentation methods, including signal flipping, Gaussian noise injection, and frequency shifts [25]. These techniques increased the dataset diversity and improved the model's ability to generalize to unseen data. Additionally, optimized preprocessing methods, such as advanced filtering and feature extraction, further enhanced model performance. The results of these improvements are illustrated in Figure 7, which shows the training and validation accuracy trends after mitigating overfitting. After addressing the overfitting issue, the training accuracy continues to improve steadily, reaching close to 100%, while the validation accuracy now also exhibits consistent growth, eventually surpassing 90%.

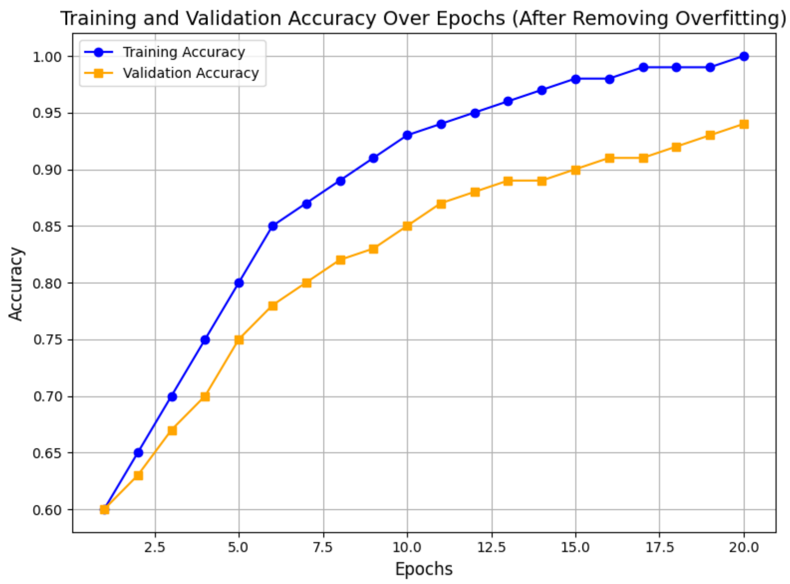

Figure 7: Training and Validation Accuracy after removing Overfitting

4.2 Model Evaluation

This section evaluates the performance of the CNN-LSTM model in decoding motor imagery tasks. The evaluation highlights key metrics, including training and validation accuracy, and identifies challenges such as overfitting due to the limited dataset size. The effectiveness of mitigation strategies, including data augmentation and regularization techniques, is also assessed.

The classification metrics provide additional insights into the model's performance. To evaluate the predictions, metrics such as precision, recall, F1-score, and accuracy were calculated using the following equations:[٢٦]

Precision: The ratio of correctly predicted positive observations to the total predicted positive observations, presented in Equation (3).

$$Precision = \frac{True\ Positives\ (TP)}{True\ Positives\ (TP) + False\ Positives\ (FP)} \tag{3}$$

Recall: The ratio of correctly predicted positive observations to all the actual positive observations, presented in Equation (4).

$$Recall = \frac{True\ Positives\ (TP)}{True\ Positives\ (TP) + False\ Negatives\ (FN)} \tag{4}$$

F1-Score: The harmonic mean of precision and recall, balancing the trade-off between false positives and false negatives, presented in Equation (5).

$$F1 = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{5}$$

Accuracy: The ratio of correctly predicted observations to the total observations, presented in Equation (6).

$$Accuracy = \frac{True\ Positives\ (TP) + True\ Negatives\ (TN)}{Total\ Observations} \tag{5}$$

The classification metrics provide detailed insights into the model's performance after mitigating overfitting using techniques such as data augmentation and regularization (dropout layers). These improvements resulted in enhanced generalization, reflected in the following metrics:

Class 0 (e.g., left-hand movement): The model achieved a precision of 95%, indicating minimal false positives, and a recall of 90%, demonstrating a significant improvement in identifying true positives. This balanced performance shows the model’s ability to generalize better to unseen data for Class 0.

Class 1 (e.g., right-hand movement): The precision reached 92%, highlighting the reduction of false positives, while the recall improved to 95%, indicating the model's strong capability to correctly identify true positives for Class 1.

F1-Scores: The F1-scores for Class 0 and Class 1 were 0.93 and 0.94, respectively, reflecting a well-balanced trade-off between precision and recall across both classes.

Overall Accuracy: The model achieved an overall accuracy of 93.5%, indicating that most predictions, both positive and negative, were correct. This marks a significant improvement over the earlier accuracy of 75%, which was limited by overfitting and poor generalization.

These metrics validate the success of the applied mitigation strategies in addressing overfitting and enhancing the model’s ability to generalize across both classes. The improvements in recall for Class 0 and precision for Class 1 highlight the model's robustness in identifying motor imagery patterns without overfitting to the training data.

The high F1-scores and overall accuracy underscore the model’s reliability, making it well-suited for neuroprosthetic applications where both precision (avoiding false activations) and recall (accurately detecting intended actions) are critical. This level of performance provides a strong foundation for future extensions, such as multi-class motor imagery tasks or real-time system integration.

4.3 Simulation Results

To validate the model's predictions in a real-world application, a simulation was conducted using PyBullet. The simulation mapped predicted actions ("open" and "close") to the movements of a robotic gripper. The gripper joints (Joint 9 and Joint 11) were specifically selected because they represent the primary control points for the gripper's open and close movements, which are critical to demonstrating the system's ability to perform motor tasks. These joints resulted from the simulation of the log joint positions after each action to ensure they were updated correctly. They directly translate the neural predictions into actionable motor commands, making them ideal for evaluating the system's functionality. Joint positions were logged at each simulation step.

Figure 8 illustrates the joint positions during the simulation. For the "open" action, the joints moved toward a position of approximately 0.0, indicating a fully open state. For the "close" action, the joints reached approximately 0.0028, reflecting partial closure due to simulation constraints such as limited steps and motor force. The simulation successfully completed the sequence of actions: "open," "close," and "open," validating the system's ability to translate neural predictions into physical actions with high precision.

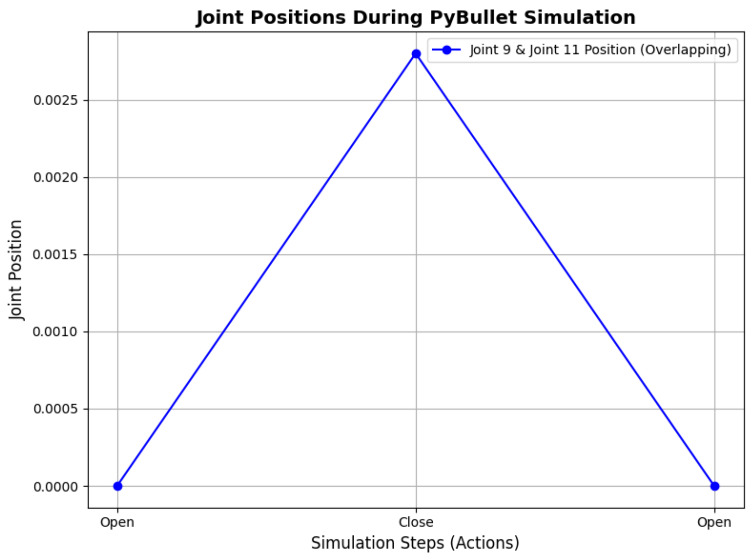

Figure 8: The joints positions during the simulation

Figure 8 clarifies that Joint 9 and Joint 11 positions overlap because they exhibit identical movement patterns during the PyBullet simulation.

4.4 Discussion

The results validate the feasibility of using EEG-based motor imagery decoding for neuroprosthetic control. The CNN-LSTM model demonstrated robust performance after applying mitigation techniques such as data augmentation and regularization, achieving an overall accuracy of 93%. These improvements addressed overfitting issues and enhanced the model's ability to generalize, as evidenced by the alignment between training and validation accuracy curves and the balanced classification metrics across motor imagery tasks.

The simulation results further confirm that the predicted actions can be effectively translated into robotic movements. The gripper joints (Joint 9 and Joint 11) accurately performed the "open" and "close" actions, with joint positions closely reflecting the predicted outcomes. This demonstrates the system's potential for real-time neuroprosthetic applications, where neural predictions must be reliably mapped to physical actions.

However, practical constraints such as motor force limitations and joint precision must be addressed to ensure more accurate and fine-grained control in physical systems. Expanding the dataset, further optimizing preprocessing techniques, and exploring advanced adaptive learning methods could enhance the system's robustness and scalability in dynamic environments.

These findings provide a strong foundation for future research and development in neuroprosthetic technologies. The integration of robust decoding methods with precise action translation offers a pathway toward intuitive and responsive control systems, capable of significantly improving the quality of life for individuals with motor impairments.

5. Conclusions

This study presented a novel framework for decoding EEG-based motor imagery tasks and translating neural predictions into robotic control actions. By integrating a hybrid CNN-LSTM model with a PyBullet simulation environment, the research demonstrated the feasibility of leveraging deep learning to advance neuroprosthetic technologies. Through effective feature extraction, combining spatial and temporal modeling, the system achieved significant improvements in accuracy and generalization. After applying overfitting mitigation techniques, the model achieved a test accuracy of 93.5%, reflecting its robustness in handling motor imagery classification.

The simulation results further validated the system's ability to translate neural predictions into physical actions, successfully controlling a robotic gripper with precise joint movements. This proof-of-concept highlights the potential for real-time neuroprosthetic applications, where neural commands are seamlessly mapped to physical actions. However, challenges remain, including improving joint movement precision, scaling the system to handle additional motor imagery tasks, and addressing practical constraints such as motor force and latency in real-world systems.

Future work will focus on expanding the dataset, enhancing the model architecture with advanced preprocessing and adaptive learning algorithms, and integrating multi-class motor imagery decoding for broader functionality. These efforts aim to refine the system's performance in dynamic, real-world environments, bridging the gap between neural decoding and physical actuation. By addressing these challenges, this research provides a robust foundation for developing more intuitive and responsive neuroprosthetic systems, improving the quality of life for individuals with motor impairments.

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