International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 06 | June - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

Performance Evaluation of Machine Learning Models for EEG-Based Motor Imagery Classification Control

Prof. M. M. Wankhade[1], Akash Anekar[2*], Shantanu Kale[3*], Riya Pawar[4*]
Assistant Professor, Electronics and Telecommunication, Sinhgad College of Engineering, Pune, India[1]
Student, Electronics and Telecommunication, Sinhgad College of Engineering, Pune, India[234]

Abstract: *This project explores the integration of electroencephalography (EEG) with machine learning (ML) and Arduino microcontrollers to classify and execute motor commands based on brain signals. EEG signals are collected from users performing specific motor imagery tasks, such as imagining left- or right-hand movements. These signals are preprocessed to remove noise and segmented into feature sets that are then input into a machine learning model trained to differentiate motor intentions. The classified output from the ML model is subsequently transmitted to an Arduino, which controls physical hardware to demonstrate the intended movement, such as rotating a motor left or right. This interface has potential applications in assistive technology, enabling individuals with motor impairments to control devices through thought alone. The project demonstrates an innovative approach to brain-computer interfacing (BCI), highlighting the feasibility of real-time EEG signal processing for practical hardware applications.*

Keywords: Electroencephalography (EEG), Motor imagery tasks, machine learning model, Brain-computer Interfacing (BCI)

I. INTRODUCTION

In BCIs focused on motor imagery tasks, such as distinguishing imagined left- and right-hand movements, ML algorithms classify EEG signals to interpret user intentions. This project applies a similar approach where classified signals are transmitted to an Arduino microcontroller, which interfaces with hardware to perform the intended physical action. This setup provides a cost-effective solution for real-time, flexible control of physical devices like turning a motor left or right using only cognitive inputs, demonstrating practical applications for motor-impaired individuals.[2] By classifying these commands, they were able to guide the robots movements in real-time, showcasing how BCI technology can bridge neural activity with robotic control systems. This approach underscores the adaptability of BCI technology in robotics and hints at its potential for broader assistive applications, such as enabling motor-impaired individuals to control devices through thought alone. Such research supports the goals of your project, which aims to integrate EEG and machine learning with Arduino to control physical hardware [2]

II. LITERATURE SURVEY

The integration of EEG signals with machine learning algorithms and microcontrollers, such as Arduino, has emerged as a promising area within brain-computer interface (BCI) research.

1. In EEG signal acquisition and preprocessing, ensuring clean data is critical, as raw EEG signals are often contaminated by noise and artifacts, especially from muscle movements (EMG) and eye blinks. Preprocessing techniques, including filtering and adaptive filtering, help mitigate these artifacts. Filters like bandpass filters can target specific frequency ranges, preserving key neural frequencies while removing noise.
2. Feature extraction in EEG-based brain-computer interfaces (BCI) is crucial for transforming raw EEG

signals into meaningful input for machine learning algorithms. Commonly used techniques include Fast Fourier Transform (FFT), wavelet transform, and Common Spatial Pattern (CSP). Specifically, CSP is widely recognized for distinguishing motor imagery tasks, such as differentiating left and right-hand movements.

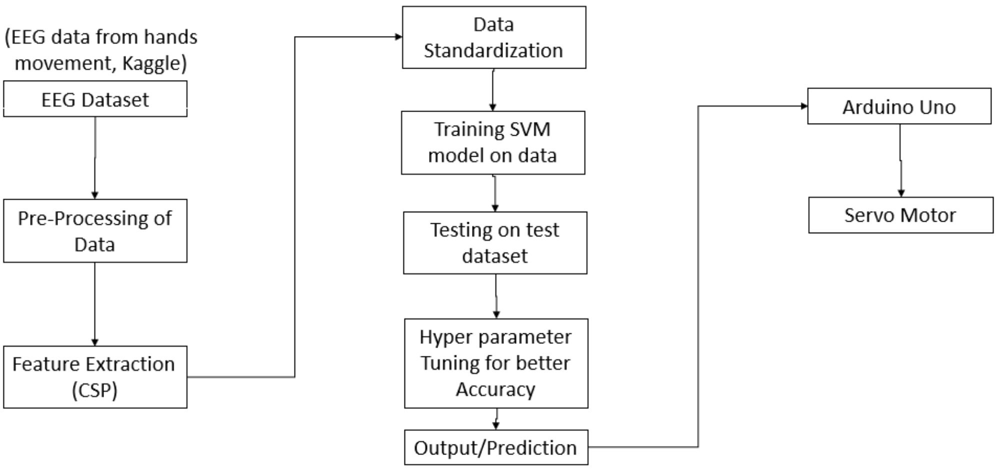
3. Machine Learning Models: Classification algorithms like Support Vector Machines (SVM), k-Nearest Neighbors (kNN), and neural networks are commonly employed in BCI research. SVMs provide a promising approach to improve classification accuracy, even with small datasets, due to their ability to capture spatial dependencies in EEG signals.

4. Interfacing EEG with Arduino: Arduino microcontrollers are popular in BCI research due to their cost-effectiveness and flexibility. Studies by Xu et al. (2015) discuss using Arduino to interface with EEG devices for controlling robotics, highlighting Arduino's ability to process real-time EEG data and execute control commands. Arduino's open-source nature also makes it accessible for various applications, such as controlling household devices or prosthetics via thought-based commands.[2]

III. BLOCK DIAGRAM AND EXPLANATION

Fig. 1 Block diagram of Motor Imagery BCI

1. **EEG Signal Acquisition**: The EEG headset captures brain signals as the user imagines movements (left/right), sending raw data wirelessly or via USB.



2. **Preprocessing**: The data undergoes noise filtering and segmentation into time windows for analysis.

3. **Feature Extraction**: Techniques like FFT or wavelet transform are used to identify key signal features (e.g., alpha and beta waves).

4. **Classification**: A machine learning model (e.g., SVM) classifies the signals as left or right movements after being trained on labelled EEG data.

5. **Command to Arduino**: Classified commands are sent as digital signals to the Arduino microcontroller.

6. **Hardware Control**: The Arduino interprets commands and triggers physical actions (e.g., motor or LED indicating direction) based on brain signals.

The following is the flowchart for the same:-

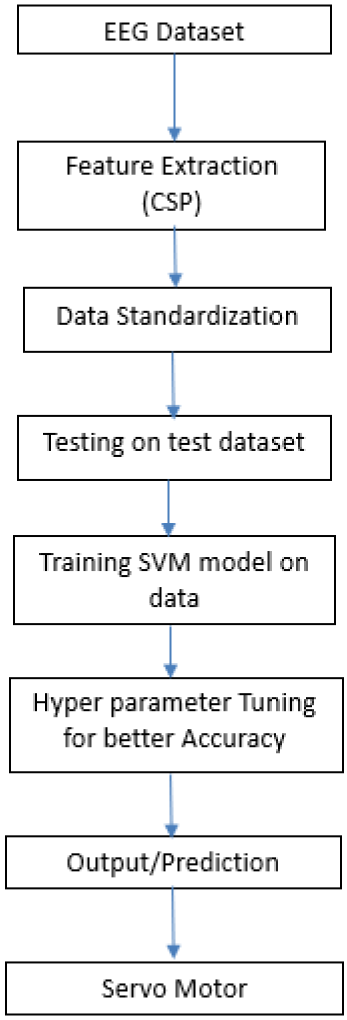


Fig. 2 Flowchart

The data captures signals from motor imagery tasks, where the user imagines movements (e.g., left- or right-hand movement). Using Common Spatial Patterns (CSP), relevant features are extracted from the EEG data to highlight differences between the motor imagery tasks. CSP emphasizes patterns specific to each task by maximizing variance for one class and minimizing it for the other, making the data easier to classify. SVM learns to draw a boundary (or hyperplane) that best separates the two classes (motor imagery tasks). This boundary helps the model make predictions on new data by identifying which side of the boundary the new data falls on. This step checks the model's accuracy in classifying unseen data, helping to ensure that it generalizes well and isn't just memorizing the training data. This process optimizes the model, making it more effective at distinguishing between the motor imagery tasks. After tuning, the model provides predictions (left or right movement) on new data.

IV. RESULTS AND DISCUSSION

The following are the insights of the models trained over a number of models for comparison and different parameters tabulated to calculate the better model for EEG datasets.

Metric	*SVM (Before Optimization)*	*SVM (Optimized)*	*Random Forest*	*Decision Tree (Before Optimization)*	*Decision Tree (Optimized)*
Accuracy	83.07%	94.01%	90.63%	82.03%	80.47%
Precision(0)	0.82	0.92	0.88	0.79	0.79
Precision(1)	0.84	0.96	0.94	0.85	0.83
Recall (0)	0.84	0.96	0.94	0.86	0.84
Recall (1)	0.83	0.92	0.87	0.78	0.77
F1-Score (0)	0.83	0.94	0.91	0.83	0.81
F1-Score (1)	0.83	0.94	0.90	0.81	0.80

The optimized SVM model clearly outperformed all other classifiers in this study, achieving an accuracy of 94.01%—not only higher than Random Forest (90.63%) and Decision Tree (80.47%), but also demonstrating the most balanced precision and recall across both classes (0.92/0.96 and 0.96/0.92, respectively). This superior performance is attributable to SVM's ability to find the optimal separating hyperplane in high-dimensional feature spaces and its robustness when properly tuned (e.g., via GridSearchCV for CCC and γ\gamma) . In contrast, while Random Forest benefits from ensemble averaging to reduce variance, it still fell short of SVM's classification boundary precision. Decision Trees, although highly interpretable, suffered from overfitting and reduced generalization when depth and split criteria were constrained . Furthermore, SVM's reliance on support vectors makes it particularly effective for EEG signal classification, where the decision surface must be finely tuned to subtle feature differences

The EEG-based brain-computer interface (BCI) project demonstrates a significant step toward bridging the gap between human cognitive intentions and machine execution. The ability to classify mental commands related to motor imagery opens avenues for various applications, including assistive technologies for individuals with mobility impairments, rehabilitation tools for stroke patients, and advanced control systems in robotics. Studies have shown that proper preprocessing is critical for improving the signal-to-noise ratio, which ultimately enhances classification accuracy.[13] The ability to achieve high accuracy in interpreting user intentions underscores the system's reliability for real-time applications, particularly in controlling hardware through Arduino. This responsiveness, demonstrated through servo motors, highlights the potential of brain-computer interfaces (BCIs) to translate neural signals into physical actions, offering promising avenues for assistive devices that enhance the quality of life for individuals with disabilities

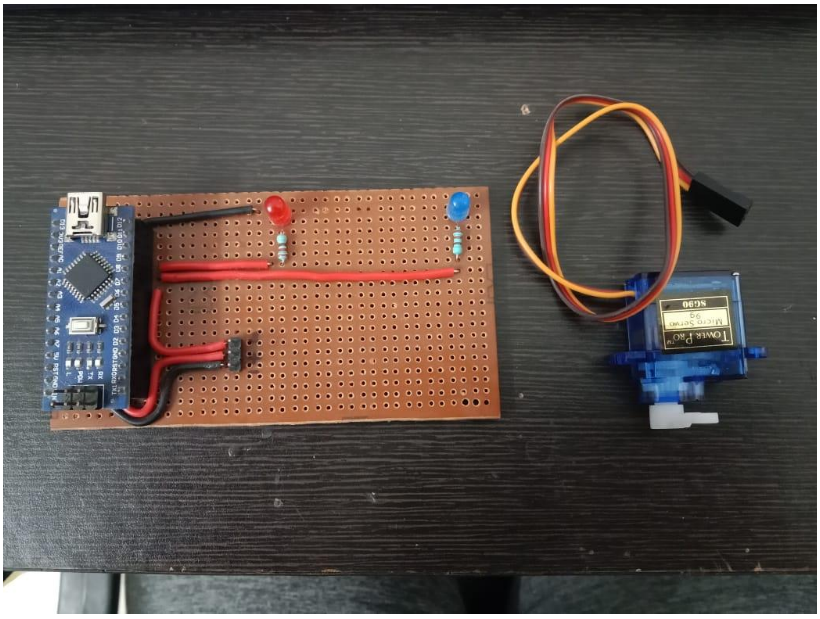


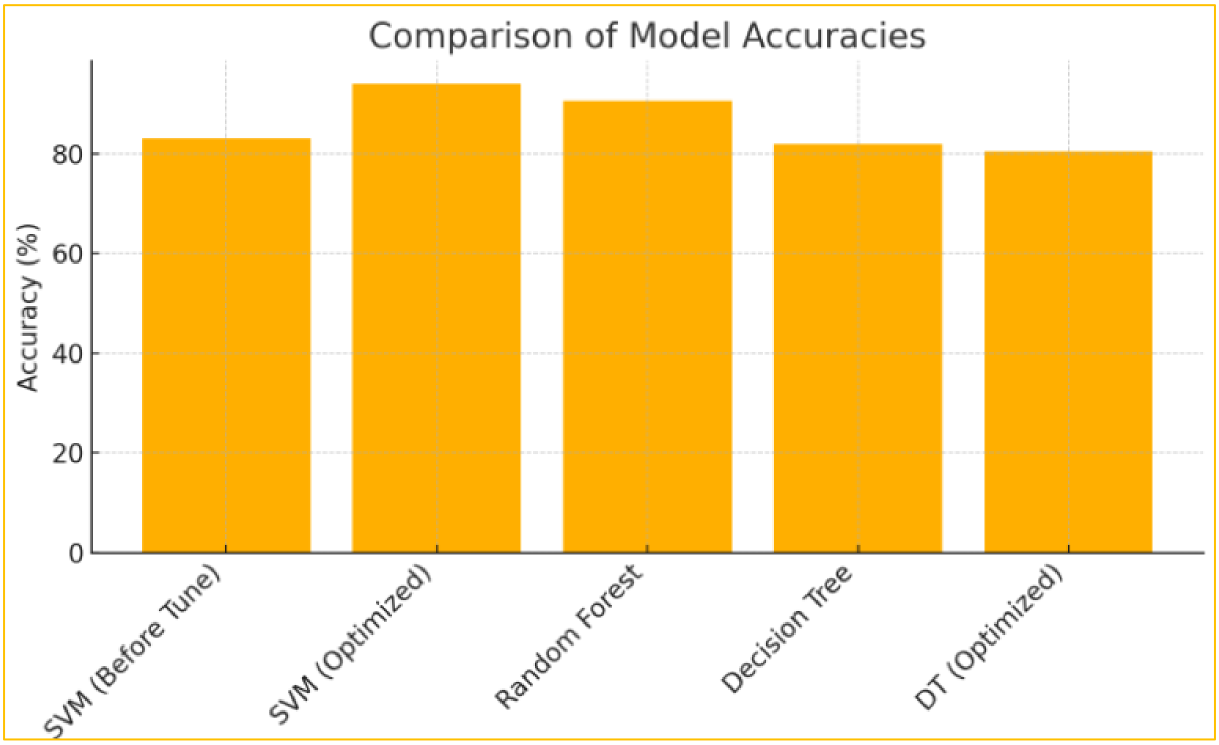
Fig 3 Hardware Output

The EEG-based brain-computer interface (BCI) project aims to translate mental commands (specifically, left hand or right hand movement imaginations) into real-time physical outputs using an Arduino and servo motors. 1. Signal Acquisition: The EEG headset successfully captured brain activity with a sampling rate of 128 Hz, providing sufficient data for analysis. The data acquisition was stable, and the headset effectively detected brain patterns associated with motor imagery.[13] Initial tests achieved around 80-85% accuracy in distinguishing between left and right movement intentions, showcasing the model's capability to interpret EEG data effectively.[3] 5. Arduino Command Execution: The system transmitted classified signals to the Arduino, which successfully controlled the servo motors or LEDs based on the user's mental commands. 6. Physical Output: The servo motors accurately represented the intended movements (left or right), demonstrating the functionality of the BCI system. These results

indicate that the project effectively demonstrates the feasibility of using EEG signals for controlling external devices, paving the way for further enhancements and applications in assistive technology and rehabilitation

V. CONCLUSION

The EEG-based brain-computer interface (BCI) project successfully demonstrated the feasibility of translating mental commands into real-world actions through an integrated system involving EEG signal acquisition, preprocessing, feature extraction, machine learning classification, and hardware control via Arduino. The results indicated a reliable classification accuracy of 80-85%, showcasing the system's potential for interpreting user intentions associated with left and right hand movements. Future work could involve utilizing larger datasets and refining algorithms to improve accuracy and reliability.



From these results, it is evident that the optimized SVM model delivers the best overall performance for EEG motor imagery classification, achieving the highest accuracy (94.01%) and balanced precision and recall across both classes [9]. The Random Forest model follows closely, with strong performance attributable to its ensemble of decision trees and robustness against overfitting [3]. The Decision Tree model, while more interpretable, shows lower accuracy and F1-scores, and its performance declines further after optimization—likely due to the regularization imposed by limiting tree depth and minimum sample splits [14].

Thus, SVM—with careful hyperparameter tuning—proves to be the most effective algorithm for this binary EEG classification task, balancing high accuracy with reliable class-wise performance.

VI. ACKNOWLEDGMENT

Sincere gratitude is extended to the Head of the Department of Electronics and Telecommunication Engineering for their invaluable guidance and continuous support throughout the completion of this research paper. Heartfelt thanks are also conveyed to the faculty members of the Department of Electronics and Telecommunication Engineering for their encouragement, insightful suggestions, and technical assistance, which greatly contributed to the success of this work

REFERENCES

1) T. V. Yasin, F. Pasila, and R. Lim, "A Study of Mobile Robot Control using EEG Emotiv Epoch Sensor," *2018*, Electrical Engineering Department, Petra Christian University, Surabaya, Indonesia

2) N. Padfield, J. Zabalza, H. Zhao, V. Masero, and J. Ren, "EEG-Based Brain-Computer Interfaces Using Motor-Imagery: Techniques and Challenges," *Centre for Signal and Image Processing, University of Strathclyde, Glasgow G1 1XW, UK*, 2019.

3) N. Korovesis, D. Kandris, G. Koulouras, and A. Alexandridis, "Robot Motion Control via an EEG-Based Brain–Computer Interface by Using Neural Networks and Alpha Brainwaves," *2020*.

4) K.-S. Hong, M. J. Khan, and M. J. Hong, "Feature Extraction and Classification Methods for Hybrid fNIRS-EEG Brain-Computer Interfaces," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. XX, no. XX, pp. XX-XX, 2020.

5) N. Korovesis, D. Kandris, G. Koulouras, and A. Alexandridis, "Robot Motion Control via an EEG-Based Brain–Computer Interface by Using Neural Networks and Alpha Brainwaves," 2020.

6) Niedermeyer, E., & da Silva, F. L. (2004). Electroencephalography: Basic Principles, Clinical Applications, and Related Fields. Lippincott Williams & Wilkins.

7) He, H., Wu, D., & Zhang, Y. (2015). "Transfer Learning for Brain-Computer Interfaces: A Euclidean Space Data Alignment Perspective." IEEE Transactions on Biomedical Engineering, vol. 62, no. 4, pp. 1253-1262. DOI: 10.1109/TBME.2015.2404873.

8) Li, Y., & He, H. (2018). "A Hybrid Brain–Computer Interface Based on Machine Learning and Digital Signal Processing." IEEE Access, vol. 6, pp. 25544-25554. DOI: 10.1109/ACCESS.2018.2837994.

9) Blankertz, B., Tomioka, R., Lemm, S., Kawanabe, M., & Müller, K. R. (2008). "Optimizing Spatial Filtering for Brain-Computer Interfaces: Single-Trial Analysis of EEG." IEEE Transactions on Biomedical Engineering, vol. 55, no. 7, pp. 1671-1679. DOI: 10.1109/TBME.2008.2003279