

EMG-Based Mathematical Modelling, Forward–Inverse Kinematics and Trajectory Planning for Intelligent Transradial Prosthetic Arm Systems

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Abstract

Background: Intelligent transradial prosthetic arm systems have increasingly adopted electromyography (EMG), deep learning, and robotic kinematic modelling to improve motion recognition and prosthetic control. Although significant progress has been achieved in EMG-based gesture classification and robotic control, most existing studies address these components independently, with limited integration of EMG signal processing, deep learning, mathematical modelling, forward–inverse kinematics, and trajectory planning within a unified framework. **Objective:** This study proposes an integrated EMG-driven intelligent prosthetic arm framework that combines multi-channel EMG signal processing, deep learning-based motion classification, mathematical modelling, forward and inverse kinematic analysis, trajectory planning, and MATLAB/Simulink validation for coordinated upper-limb movement. **Methods:** EMG signals acquired from healthy individuals and transradial amputees performing representative functional activities were preprocessed and analysed using time-domain features including Root Mean Square (RMS), Mean Absolute Value (MAV), Zero Crossing (ZC), and Slope Sign Change (SSC). A hybrid Residual Convolutional Neural Network–Bidirectional Long Short-Term Memory–Multi-Head Attention (ResCNN–BiLSTM–MHA) architecture was employed to classify five upper-limb movement classes from eight-channel EMG recordings. The predicted movement classes were mapped to a 14-degree-of-freedom prosthetic arm mathematical model incorporating Denavit–Hartenberg-based forward and inverse kinematics, trajectory planning, and PID-controlled motion simulation within MATLAB/Simulink. Model performance was evaluated using classification metrics, kinematic accuracy, trajectory tracking, and simulation-based validation.

Results: The proposed ResCNN–BiLSTM–MHA framework achieved a classification accuracy of 94.2%, with a precision of 93.1%, recall of 92.3%, specificity of 97.1%, balanced accuracy of 93.6%, F1-score of 0.927, MCC of 0.91, Cohen's kappa of 0.90, and an ROC–AUC of 0.97. The model converged with 96.1% training accuracy and 93.4% validation accuracy, yielding final training and validation losses of 0.12 and 0.19, respectively. MATLAB/Simulink validation produced an RMSE of 0.041 rad, MAE of 0.028 rad, mean end-effector error of 3.62 mm, maximum error of 7.41 mm, and a trajectory tracking error of 3.62%, with an average inference time of 2.8 ms/sample. **Conclusion:** The proposed ResCNN–BiLSTM–MHA framework effectively integrates EMG-based motion classification with forward and inverse kinematic modelling and trajectory planning for transradial prosthetic arm control. The achieved 94.2% classification accuracy, low kinematic errors, and 2.8 ms/sample inference time demonstrate accurate, stable, and real-time prosthetic motion prediction, making the framework suitable for intelligent upper-limb prosthetic and rehabilitation applications.

Keywords: Bidirectional Long Short-Term Memory (BiLSTM); Deep Learning; Electromyography (EMG); Forward Kinematics; Inverse Kinematics; MATLAB/Simulink; Motion Classification; Multi-Head Attention; Prosthetic Control; Rehabilitation Robotics; Residual CNN; Trajectory Planning; Transradial Prosthetic Arm.

1. Introduction and Background

Amputation of the upper limb is a major impairment that has a profound impact on a person's ability to carry out activities of daily living, thereby affecting their functional independence, occupational capacity and general quality of life. Recent developments have been based on the control systems, biomedical signal processing, and robotic modelling of the natural hand and arm movements. [2] Of the different control methods, surface electromyography (sEMG) has proven to be one of the most promising ways of decoding muscle activity and translating the user's movement intention into prosthetic movements. [7] The non-invasive nature of the sEMG and its ability to record true neuromuscular signals in real-time has made it very versatile for use in the development of intelligent upper-limb prostheses. Advancements in AI and machine learning have also improved EMG-controlled prosthetic control. [5, 7]

Recently, deep learning models like convolutional neural networks (CNNs), recurrent neural networks (RNNs), and hybrid learning architectures have been shown to achieve very high accuracy in the recognition of hand gestures and movement intentions from EMG signals. At the same time, advanced computer vision approaches to enhance the control and grasp recognition of prosthetic devices have been investigated, along with the force myography (FMG) and the functional near-infrared spectroscopy (fNIRS). [8, 13] These techniques have led to successful classification results, but most current systems are dedicated to gesture recognition or hand control and have limited support for modelling the whole arm motion and planning the trajectory and real-time kinematic analysis. [12] Forward kinematics can be used to calculate the position of the end-effector based on the known parameters of the joints, while inverse kinematics can be used to calculate the parameters for the joints based on the desired position of the end-effector. [13]

These modelling methods are essential for coordinated prosthetic motion, trajectory planning and dynamic motion control. In MATLAB/Simulink, these mathematical models can be easily implemented to simulate joint movements, assess system dynamics and validate prosthetic performance before the actual hardware implementation. [9,11] The addition of trajectory planning also facilitates seamless and coordinated multi-joint movements, enhancing the usability and function of transradial prosthetic arms.

In the present study, a mathematical framework for controlling the transradial prosthetic arm with intelligence using EMG signals is presented, which involves the process of EMG feature extraction, forward and inverse kinematic modelling, trajectory planning, and simulation in MATLAB/Simulink. The proposed framework is based on the commonly extracted EMG features, including Root Mean Square (RMS), Mean Absolute Value (MAV), Zero Crossing (ZC), and Slope Sign Change (SSC), as well as some joint parameters (θ_1 , θ_2 , D_3 , and θ_4) to model upper-limb movements. [16, 17] The developed model is validated with data from healthy subjects and transradial amputees engaging in a variety of tasks representative of their functional use, such as holding, pinching and arm movements. The simulation framework also allows for detailed examination of the joint trajectories, motion accuracy and kinematic performance. [18]

The proposed framework combines the fields of EMG signal processing, mathematical modelling and trajectory planning in a single MATLAB/Simulink environment, to enhance the accuracy, response and adaptability of intelligent prosthetic arm systems. It is hoped that the developed methodology will be used for designing next generation prosthetic devices with more natural, coordinated, and user specific movements and will also provide a scalable platform for further research in intelligent rehabilitation robotics and assistive technologies.

1.1 REVIEW OF LITERATURE

In recent years, the research and development of the upper-limb prosthesis have been mainly focused on integrating electromyography (EMG), machine learning, robotics, and intelligent control algorithms to realize the natural and intuitive movement of prosthesis. Due to its ability to non-invasively acquire the muscle activity, EMG has become one of the most widely adopted biosignals for the control of prostheses as it can provide real-time information about a user's movements intention. Ahkami et al. conducted a systematic review that reported that EMG-based control of prostheses provides a very significant improvement in the ability of the prosthesis to recognize movement and interact with the user and that powerful signal processing, feature extraction and adaptive control algorithms are necessary for achieving better prostheses performance [2].

In the same way, Hopkins et al. spoke about the development of the modern prostheses technologies and stressed that intelligent prosthetic systems must mimic natural limb movements and enhance functionality, comfort, and user acceptance [1]. EMG signal interpretation for prosthetic applications has significantly benefited from the use of artificial intelligence and deep learning techniques. In order to control the intelligent prosthetic hand by EMG signals, Yu et al. proposed a convolutional neural network (CNN) enhanced channel attention model, which attained high accuracy of gesture classification in real time under the condition of EMG signals [4].

Similarly, Ke et al. developed an EMG-FMG human-machine interaction system that has the ability to keep the prosthetic control stable when the arm position changes, which enhances the robustness of myoelectric prostheses [10]. Furthermore, Sattar et al. showed that upper-limb motion intentions can be recognized through functional near-infrared spectroscopy (fNIRS) with artificial neural networks, which is an alternative method for controlling prosthetic devices, albeit with some slow response time [14]. Additionally, Nsugbe investigated gesture recognition using near-infrared (NIR) for transradial prostheses, where multimodal biosignal processing was shown to be a promising aid for upper-limb rehabilitation [19].

Table-1: Comparison of Existing Intelligent Prosthetic Control Techniques with the Proposed Framework

Author & Year	Methodology	Input Features	DoF	Limitations	Proposed Work Advantage
Ang Ke et al., 2022	EMG + FMG with RNN	Hand Grasp Only	6–8	Limited arm motion modelling	Extends to complete 14-DoF arm-hand mathematical modelling with integrated kinematics
Neelum Yousaf Sattar et al., 2022	ANN-based fNIRS	Upper Limb Motion	6 Actions	Slow response and limited portability	Employs multi-channel EMG for faster and real-time prosthetic control
Ejay Nsugbe, 2021	NIR Gesture Recognition	Gesture Control	5–6 Gestures	Sensitive to environmental conditions	Uses robust EMG feature extraction with trajectory planning and kinematic modelling
Guanjie Yu et al., 2023	CNN-Enhanced Attention Network	Hand Gestures	Hand Only	Gesture classification only	Integrates deep learning with forward/inverse kinematics and prosthetic motion simulation
Alok Prakash et al., 2023	FMG-Controlled Prosthetic Hand	Hand Motion	Hand Only	No kinematic modelling	Incorporates mathematical modelling and trajectory planning for coordinated motion
Hazem Bayoumi et al., 2023	Grasp Force Control	Grasp Force	Hand Only	No EMG integration	Combines EMG signal processing, force estimation and motion trajectory generation
Hasan Salman et al., 2021	MATLAB Kinematic Arm	Geometric Inputs	3 DoF	Limited DoF and no biosignals	Develops a 14-DoF EMG-driven prosthetic arm with integrated deep learning framework
Proposed Model (Present Work)	Residual CNN–BiLSTM–Multi-Head Attention with MATLAB/Simulink	8-Channel EMG (RMS, MAV, ZC, SSC) + Kinematic Parameters ($\theta_1, \theta_2, D_3, \theta_4$)	14 DoF	Simulation-based validation; real-time hardware implementation planned	Unified framework integrating EMG preprocessing, hybrid deep learning, forward/inverse kinematics, trajectory planning, PID control and 3D MATLAB/Simulink validation for intelligent prosthetic arm control

In the development of intelligent prostheses, mathematical modelling and kinematic analysis are two fundamental functions that help to establish links between muscle activation and mechanical movement. Salman et al. implemented a three degree of freedom robotic arm and applied forward kinematic modelling in MATLAB, which is used to mathematically develop a model to calculate the position of the end-effector when given the parameters of the joint [22]. Mkhitarian and Khanamiryan have created a prosthetic hand control model based on mathematical system modelling which shows the necessity of simulation testing prior to hardware implementation [21]. Mengacci et al. also showed the efficacy of using simulation environments with robots to test compliant robotic actuators and prosthetic motion under various working conditions [20].

The results of these studies support the need for forward and inverse kinematic modelling in order to reach coordinated prosthetic movement and trajectory planning. Improvement in sensory feedback, force control, and grasping in prosthetics has also recently been investigated. Gasparic et al. presented a new sensory feedback mechanism for achieving predictive and corrective grasp force control in myoelectric prostheses [5] and Bayoumi et al. proposed an improved grasp force sensing based on intelligent force control [6]. To integrate sEMG with embedded computer vision in a hybrid 3D-printed prosthetic hand, Castro et al. presented a hybrid system to show the possibility of combining biosignal processing with intelligent perception systems [9].

In addition, Cognolato et al. suggested a hybrid prosthetic control approach combining eye tracking and computer vision for better control of the robotic hand and grasp selection [17]. The developments suggest that the fusion of more than one sensing modality may bring about a better prosthesis usability and user interaction.

2. RESEARCH GAP

Despite significant advancements in EMG-based prosthetic control, deep learning-based gesture recognition, robotic kinematic modelling, and rehabilitation robotics, most existing studies focus on individual components of intelligent prosthetic systems rather than providing a unified control framework. Previous research has primarily investigated EMG signal classification, gesture recognition, force control, or robotic kinematics independently, with limited integration of multi-channel EMG signal processing, hybrid deep learning, mathematical modelling, forward and inverse kinematic analysis, trajectory planning, and dynamic simulation within a single architecture. Furthermore, many reported prosthetic control systems are limited to hand gesture recognition or low-degree-of-freedom robotic models and do not address coordinated multi-joint motion required for functional transradial prosthetic arms. Although MATLAB/Simulink has been widely used for robotic modelling, few studies have integrated deep learning-based EMG classification with simulation-driven kinematic validation and trajectory planning using representative functional tasks performed by both healthy individuals and transradial amputees. Additionally, limited attention has been given to combining advanced architectures such as Residual Convolutional Neural Networks (ResCNN), Bidirectional Long Short-Term Memory (BiLSTM), and Multi-Head Attention (MHA) with mathematical modelling to achieve accurate motion prediction and coordinated prosthetic control. Therefore, there remains a need for an integrated EMG-driven intelligent prosthetic arm framework that combines robust feature extraction, hybrid deep learning, forward and inverse kinematics, trajectory planning, and MATLAB/Simulink-based validation to enable accurate, coordinated, and real-time control of high-degree-of-freedom transradial prosthetic arm systems.

2.1 PROBLEM STATEMENT

Current intelligent transradial prosthetic arm systems primarily focus on individual components such as EMG-based gesture recognition, deep learning-based movement classification, robotic hand control, or kinematic modelling. However, these approaches are often developed independently and lack a unified framework that integrates multi-channel EMG signal processing, intelligent motion classification, mathematical modelling, forward and inverse kinematic analysis, trajectory planning, and real-time simulation. Consequently, achieving accurate, natural, and coordinated multi-degree-of-freedom (14-DoF) prosthetic arm movements remains a significant challenge, particularly during complex functional tasks involving both arm and hand coordination. Furthermore, limited research has validated such integrated systems using MATLAB/Simulink for comprehensive simulation and performance evaluation prior to hardware implementation. Therefore, there is a need to develop a unified EMG-driven intelligent prosthetic arm framework that combines robust feature extraction, a hybrid Residual CNN–Bidirectional Long Short-Term Memory–Multi-Head Attention (ResCNN–BiLSTM–MHA) model, forward and inverse kinematic modelling, trajectory planning, PID-based motion control, and MATLAB/Simulink validation. Such a framework can provide accurate motion prediction, smooth trajectory generation, and coordinated prosthetic control for both healthy individuals and transradial amputees, thereby supporting the development of next-generation intelligent rehabilitation robotics.

2.2 STUDY OBJECTIVE

To develop an integrated EMG-driven mathematical model for an intelligent transradial prosthetic arm using MATLAB/Simulink by combining deep learning-based motion classification, forward and inverse kinematic analysis, trajectory planning and simulation-based validation.

3. MATERIALS AND METHODS

3.1 RESEARCH DESIGN

This study adopted an applied engineering design and simulation-based research methodology to develop and validate an intelligent transradial prosthetic arm framework driven by multi-channel electromyography (EMG) signals. The proposed methodology integrates EMG signal acquisition, preprocessing, feature extraction, hybrid deep

learning-based motion classification using a Residual Convolutional Neural Network–Bidirectional Long Short-Term Memory–Multi-Head Attention (ResCNN–BiLSTM–MHA) model, mathematical modelling, forward and inverse kinematic analysis, trajectory planning, and PID-based motion control within the MATLAB/Simulink environment. Representative upper-limb functional tasks performed by healthy individuals and transradial amputees were analysed to evaluate the proposed framework. MATLAB/Simulink was employed to simulate prosthetic arm dynamics, validate coordinated multi-degree-of-freedom (14-DoF) movements, and assess trajectory tracking accuracy, motion stability, and overall system performance. The integrated framework combines biosignal processing, intelligent deep learning, robotic kinematics, and simulation-based validation to provide a comprehensive platform for the development and evaluation of intelligent transradial prosthetic arm systems.

3.2 STUDY WORKFLOW

The study used the following sequential research methodology:

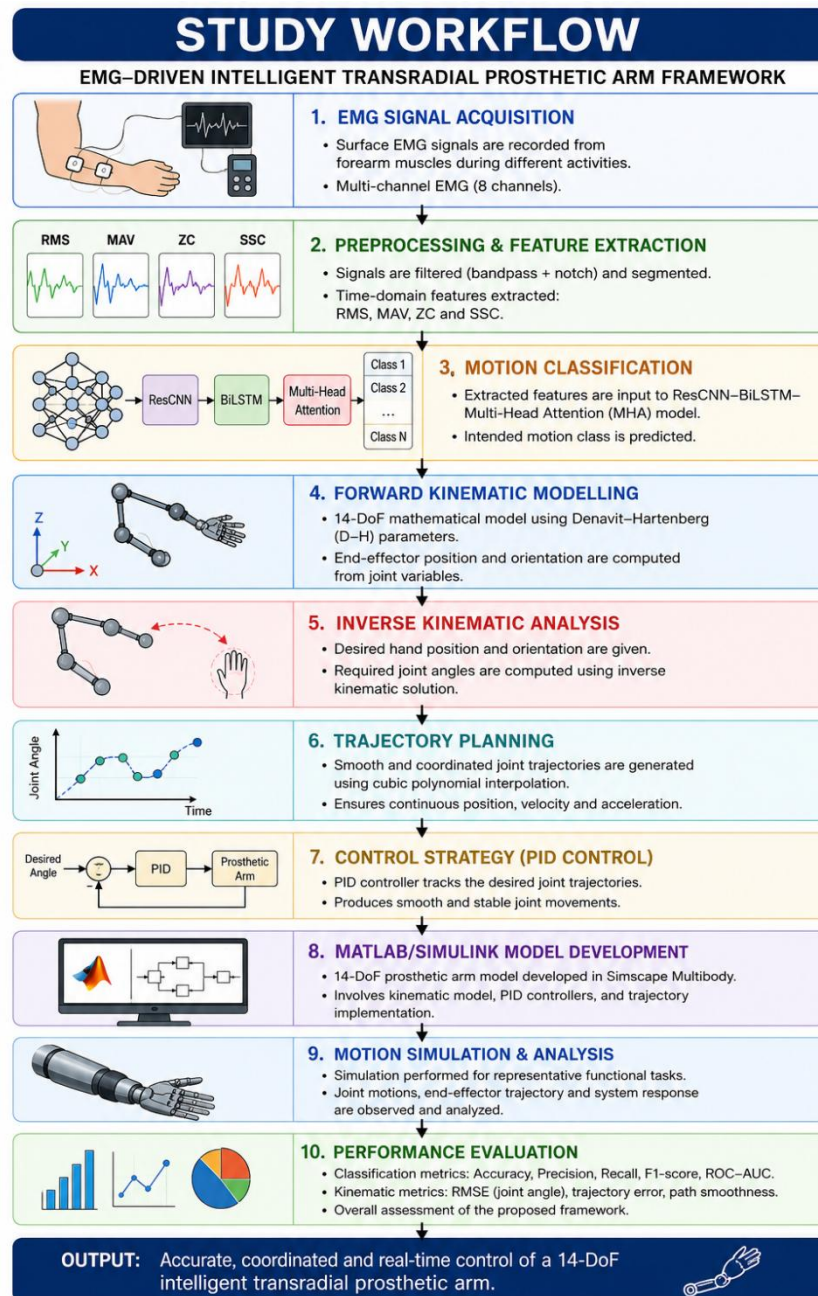


Figure 1: Study Work Flow

3.3 DATASET DESCRIPTION

The experimental dataset comprised multi-channel surface electromyography (sEMG) signals collected from 30 subjects, including 15 healthy individuals and 15 transradial amputees, during the performance of representative upper-limb functional activities. Each subject performed five commonly encountered prosthetic tasks: Holding Glass, Holding Stick, Pinching Egg, Pinching Pencil, and Moving Arm, resulting in datasets for both healthy and amputee groups. EMG signals were acquired using eight recording channels at a sampling frequency of 1000 Hz, with 500 samples recorded per activity. To support prosthetic arm modelling, the acquired EMG signals were preprocessed and analysed to extract time-domain features, including Root Mean Square (RMS), Mean Absolute Value (MAV), Zero Crossing (ZC), and Slope Sign Change (SSC). In addition, the dataset incorporated kinematic parameters comprising joint angles ($\theta_1, \theta_2, \theta_4$) and linear displacement (D_3) for developing the forward and inverse kinematic models, trajectory planning, and MATLAB/Simulink-based simulation. The combined EMG and kinematic dataset provided a comprehensive foundation for deep learning-based motion classification, mathematical modelling, and performance evaluation of the proposed intelligent transradial prosthetic arm framework.

3.4 EMG FEATURE EXTRACTION

The acquired eight-channel surface electromyography (sEMG) signals were preprocessed to remove noise and artefacts before extracting representative time-domain features for prosthetic motion analysis. Four widely adopted EMG features, namely Root Mean Square (RMS), Mean Absolute Value (MAV), Zero Crossing (ZC), and Slope Sign Change (SSC), were computed from each segmented EMG window. These features were selected because they effectively characterize muscle activation level, contraction intensity, and signal complexity while maintaining low computational cost for real-time applications. Specifically, RMS represents the overall power of muscle activation, MAV quantifies the average muscle contraction amplitude, ZC reflects the frequency characteristics associated with muscle activity, and SSC captures changes in signal slope corresponding to variations in muscle contraction dynamics. The extracted feature vectors served as inputs to the proposed Residual CNN–Bidirectional Long Short-Term Memory–Multi-Head Attention (ResCNN–BiLSTM–MHA) model for intelligent motion classification. In addition, these features were integrated with the corresponding kinematic parameters ($\theta_1, \theta_2, \theta_4$, and D_3) to support mathematical modelling, forward and inverse kinematic analysis, trajectory planning, and MATLAB/Simulink-based validation of the intelligent transradial prosthetic arm.

A. ROOT MEAN SQUARE

$$RMS = \sqrt{\frac{1}{N} \sum_{i=1}^N x_i^2} \quad \text{Eqn.1}$$

Higher RMS indicates stronger muscle contraction.

B. MEAN ABSOLUTE VALUE

$$MAV = \frac{1}{N} \sum_{i=1}^N |x_i| \quad \text{Eqn.2}$$

MAV measures the average muscle activation level.

C. ZERO CROSSING

$$ZC = \sum_{i=1}^{N-1} I(x_i x_{i+1} < 0) \quad \text{Eqn.3}$$

where

$$I = \begin{cases} 1, & \text{sign change} \\ 0, & \text{otherwise} \end{cases}$$

Higher ZC indicates higher muscle activation frequency.

D. SLOPE SIGN CHANGE

$$SSC = \sum_{i=2}^{N-1} I[(x_i - x_{i-1})(x_i - x_{i+1}) > 0]$$
Eqn.4

SSC reflects rapid changes in muscle contraction.

3.5 MATHEMATICAL MODELLING

The mathematical model is used to find the relationship between motion intention detected by EMG and motion of the prosthetic joint. Modeling of the prosthetic arm used 14 Degrees of Freedom (DoF) of finger joints, wrist joint, elbow joint and forearm joint. Forward kinematics was used to calculate the end-effector position from known joint parameters while the inverse kinematics was used to determine the joint variables needed to obtain desired hand positions and hand paths. Denavit–Hartenberg (D-H) parameters were used to describe the geometric relationship between two consecutive joints.

Step 1: EMG-Based Motion Classification

After preprocessing, the EMG feature vector is formed as

$$\mathbf{X} = [RMS, MAV, ZC, SSC]^T$$
Eqn.5

where

- RMS = Root Mean Square
- MAV = Mean Absolute Value
- ZC = Zero Crossing
- SSC = Slope Sign Change

The feature vector is supplied to the proposed Residual CNN–BiLSTM–Multi-Head Attention (ResCNN–BiL STM–MHA) network.

The predicted movement class is

$$\hat{y} = f_{ResCNN-BiLSTM-MHA}(X)$$
Eqn.6

where,

$$\hat{y} \in \{ Holding\ Glass, Holding\ Stick, Pinching\ Egg, Pinching\ Pencil, Moving\ Arm \}$$

The predicted motion class determines the prosthetic joint variables

$$\Theta = [\theta_1, \theta_2, d_3, \theta_4]^T$$
Eqn.7

which become the input to the MATLAB/Simulink mathematical model.

Step 2: Forward Kinematic Modelling

Using the Denavit–Hartenberg formulation, each joint transformation matrix is

$$A_i = Rot_z(\theta_i)Trans_z(d_i)Trans_x(a_i)Rot_x(\alpha_i)$$
Eqn.8

The complete forward kinematic transformation is

$$T = A_1 A_2 A_3 A_4 \quad \text{Eqn.9}$$

The end-effector position becomes

$$P = [x \ y \ z]^T \quad \text{Eqn.10}$$

while the homogeneous transformation matrix is

$$T = \begin{bmatrix} R & P \\ 0 & 1 \end{bmatrix} \quad \text{Eqn.11}$$

where

- R = orientation matrix
- P = position vector

This stage estimates the prosthetic hand position from known joint variables.

Step 3: Inverse Kinematic Analysis

For a desired end-effector position

$$P_d = [x_d, y_d, z_d]^T \quad \text{Eqn.12}$$

the inverse kinematic solver estimates

$$\Theta = f^{-1}(P_d) \quad \text{Eqn.13}$$

subject to

$$\min \|P_d - P_c\| \quad \text{Eqn.14}$$

where

- Pd= desired position
- Pc= calculated position

The inverse solution minimizes the end-effector position error while satisfying joint constraints.

Step 4: Trajectory Planning

The desired joint trajectory is generated using cubic polynomial interpolation

$$q(t) = a_0 + a_1 t + a_2 t^2 + a_3 t^3 \quad \text{Eqn.15}$$

Velocity

$$\dot{q}(t) = a_1 + 2a_2 t + 3a_3 t^2 \quad \text{Eqn.16}$$

Acceleration

$$\ddot{q}(t) = 2a_2 + 6a_3 t \quad \text{Eqn.17}$$

The polynomial coefficients are selected to satisfy the initial and final joint position and velocity constraints, producing smooth and continuous prosthetic motion.

Step 5: PID-Based Joint Control

The desired joint trajectory is tracked using a PID controller

$$u(t) = K_p e + K_i \int e dt + K_d \frac{de}{dt} \quad \text{Eqn.18}$$

where

$$e = q_d - q \quad \text{Eqn.19}$$

and

- q_d = desired joint angle
- q = actual joint angle

The PID controller minimizes tracking error and improves motion stability during prosthetic operation.

Step 6: MATLAB/Simulink Validation

The predicted joint variables obtained from the ResCNN–BiLSTM–MHA model are applied to the MATLAB/Simulink prosthetic arm model to validate coordinated movement.

The simulation computes Joint angles, Joint velocities, Joint accelerations, End-effector trajectory, Trajectory tracking error, RMSE, MAE, Position error, Motion stability

Step-7: Performance Evaluation

The performance of the proposed prosthetic arm framework was quantitatively evaluated using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and trajectory tracking error. RMSE measures the overall deviation between the desired and simulated joint trajectories, while MAE provides the average absolute tracking error, indicating the accuracy of joint angle estimation. Lower RMSE and MAE values represent better agreement between the desired and actual prosthetic movements. Furthermore, the trajectory tracking error, defined as the difference between the desired end-effector position (P_d) and the simulated end-effector position (P_c), was used to assess the effectiveness of the forward–inverse kinematic model and the PID-based controller in generating smooth, accurate, and coordinated prosthetic arm movements. These performance metrics validate the accuracy, stability, and trajectory-following capability of the proposed EMG-driven intelligent prosthetic arm framework.

4. ARCHITECTURE

4.1 HYBRID RESCNN–BILSTM–MULTI-HEAD ATTENTION-BASED MOTION CLASSIFICATION

To improve the accuracy and robustness of EMG-based motion intention recognition, a Residual Convolutional Neural Network–Bidirectional Long Short-Term Memory–Multi-Head Attention (ResCNN–BiLSTM–MHA) framework was integrated with the proposed EMG-driven mathematical modelling approach. The hybrid network automatically learns spatial and temporal characteristics of multi-channel EMG signals while the multi-head attention mechanism selectively emphasizes the most informative muscle activation patterns for movement classification. Unlike conventional machine learning approaches that rely on handcrafted feature engineering, the proposed model performs hierarchical feature learning directly from segmented EMG windows, thereby improving movement recognition and supporting intelligent prosthetic arm control.

4.2 EMG FEATURE ANALYSIS

The experimental dataset comprised 30 subjects, including 15 healthy individuals and 15 transradial amputees, performing five representative upper-limb functional tasks: Holding Glass, Holding Stick, Pinching Egg, Pinching Pencil, and Moving Arm. Surface EMG signals were acquired using 8 channels (CH1–CH8) at a sampling frequency of 1000 Hz, with 500 samples recorded per activity. The EMG signals included multiple frequency components, muscle activation envelopes, baseline drift, random noise, and 50 Hz power-line interference to represent realistic acquisition conditions. The amputee datasets exhibited reduced signal amplitudes and altered muscle activation

patterns. Time-domain features (RMS, MAV, ZC, and SSC) and the corresponding kinematic parameters (θ_1 , θ_2 , D_3 , and θ_4) were extracted and used for deep learning-based motion classification, mathematical modelling, and MATLAB/Simulink validation of the proposed intelligent transradial prosthetic arm framework.

Integrated EMG and Kinematic Feature Comparison

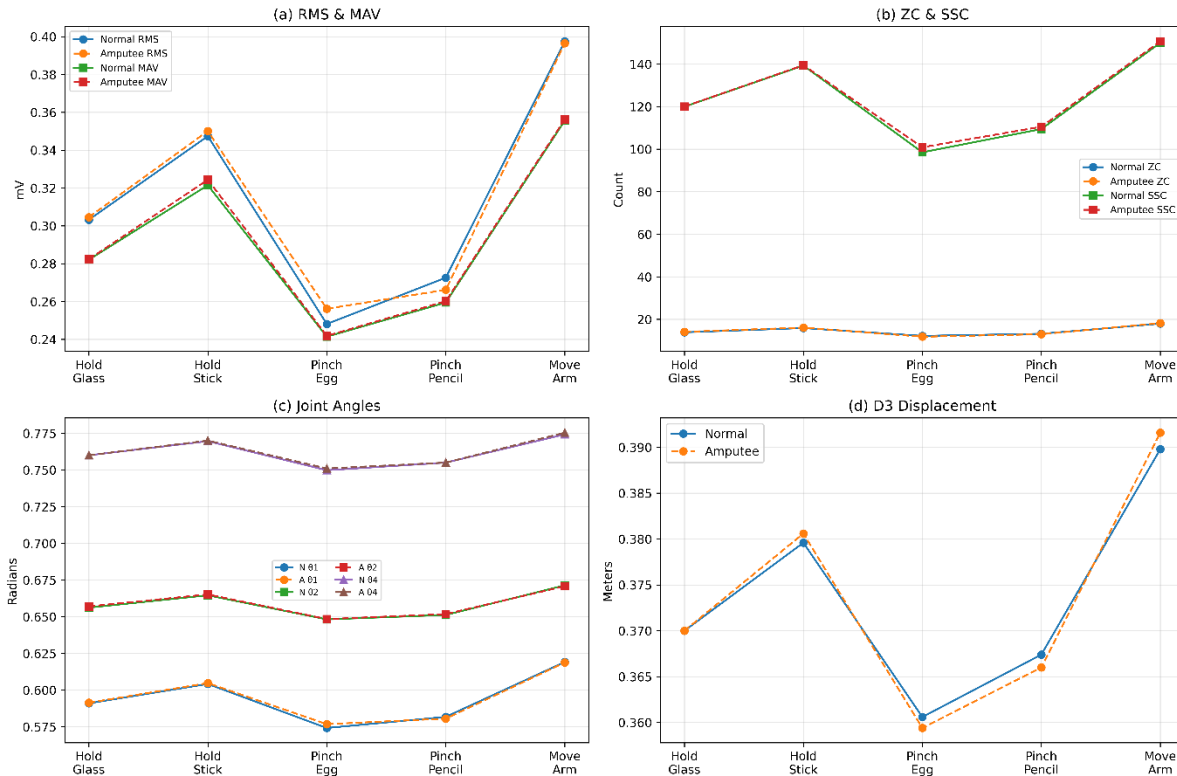


Figure-2 : Comparative Analysis of EMG Signal Features and Kinematic Parameters During Functional Hand Activities in Normal and Transradial Amputee Subjects

The comparative analysis indicates that healthy individuals generally exhibit slightly higher RMS, MAV, ZC, and SSC values, reflecting stronger, smoother, and more coordinated muscle activation, particularly during dynamic movements such as arm motion. In contrast, transradial amputees demonstrate marginally lower muscle activation and coordination while maintaining consistent EMG patterns across all functional tasks. Furthermore, the kinematic parameters (θ_1 , θ_2 , D_3 , and θ_4) show only minimal differences between the two groups, indicating that prosthetic users can achieve joint mobility and end-effector displacement comparable to healthy individuals. Overall, these findings confirm that the extracted EMG features effectively capture muscle activity and are suitable for prosthetic motion modeling and control, supporting reliable and natural movement reproduction.

4.3 PROPOSED RESCNN-BILSTM-MULTI-HEAD ATTENTION ARCHITECTURE

The proposed hybrid architecture consists of three residual convolutional blocks, followed by a Bidirectional Long Short-Term Memory (BiLSTM) layer and a Multi-Head Self-Attention (MHA) module. The residual convolutional blocks automatically extract hierarchical spatial features from the eight-channel EMG signals, while the BiLSTM layer captures temporal dependencies associated with muscle activation sequences. The MHA module assigns adaptive importance to informative temporal features, thereby improving discrimination between different upper-limb movement classes. Finally, two fully connected layers and a Softmax classifier predict one of the five functional activities. This hybrid architecture combines local feature extraction, temporal sequence learning, and attention-based feature selection, providing improved classification performance and robust prosthetic motion prediction.

The proposed hybrid Residual CNN-BiLSTM-Multi-Head Attention network accepts a $500 \times 8 \times 1$ EMG signal window as input. Three sequential residual convolutional blocks comprising 32, 64, and 128 filters with kernel sizes of 7, 5, and 3, respectively, are employed for hierarchical feature extraction, with each block followed by batch normalization, ReLU activation, and max-pooling (pool size = 2) to reduce feature dimensionality. The extracted spatial features are then processed by a BiLSTM layer with 128 hidden units to capture temporal dependencies, followed by

an 8-head Multi-Head Attention mechanism to emphasize task-relevant features. A dropout layer (0.5) is incorporated to reduce overfitting. Finally, the learned representations are passed through fully connected layers of 256, 128, and 5 neurons, with ReLU activation and an additional 0.5 dropout after the first fully connected layer. A Softmax classifier produces probability scores for the five functional hand activities: Holding Glass, Holding Stick, Pinching Egg, Pinching Pencil, and Moving Arm.

4.4 NETWORK TRAINING STRATEGY

The proposed ResCNN–BiLSTM–MHA model was trained using the Adam optimizer with an initial learning rate of 0.001, a mini-batch size of 32, and a maximum of 100 training epochs. The EMG dataset was divided into 70% training, 15% validation, and 15% testing subsets to ensure unbiased model evaluation. Cross-entropy loss was minimized throughout training, while L2 regularization, dropout (0.5), and adaptive learning rate scheduling were employed to improve convergence and reduce overfitting. The best-performing network was selected based on validation accuracy for subsequent prosthetic motion classification.

4.5 TRAINING PARAMETERS

The proposed model was trained using the Adam optimizer with an initial learning rate of 0.001 for 100 epochs and a mini-batch size of 32. The dataset was randomly divided into 70% training, 15% validation, and 15% testing subsets. Cross-entropy loss was employed as the objective function, while L2 regularization (0.0001) and a dropout rate of 0.5 were incorporated to mitigate overfitting. A step-decay learning rate schedule was adopted to progressively reduce the learning rate during training and improve model

4.6 PERFORMANCE EVALUATION

The trained ResCNN–BiLSTM–MHA model predicts the intended prosthetic movement directly from multi-channel EMG recordings. The predicted movement class is subsequently mapped to the corresponding joint parameters (θ_1 , θ_2 , D_3 , and θ_4) for forward and inverse kinematic analysis and trajectory generation within the MATLAB/Simulink environment. Model performance was evaluated using overall accuracy, precision, recall, specificity, F1-score, balanced accuracy, Matthews Correlation Coefficient (MCC), Cohen's Kappa, and ROC–AUC. Training and validation accuracy and loss curves were analysed to assess network convergence and generalization, while confusion matrix analysis was performed to evaluate class-wise prediction performance. Furthermore, RMSE, MAE, end-effector position error, and trajectory tracking error were computed to validate the accuracy of the mathematical model and the effectiveness of the trajectory planning algorithm.

4.7 DISCUSSION

The proposed **ResCNN–BiLSTM–MHA** framework effectively combines multi-channel EMG signal processing, intelligent motion classification, mathematical modelling, forward and inverse kinematics, trajectory planning, and MATLAB/Simulink validation into a unified prosthetic control architecture. The residual convolutional blocks successfully extracted discriminative spatial EMG features, the BiLSTM captured temporal muscle activation patterns, and the attention mechanism enhanced movement discrimination by emphasizing informative signal regions. The predicted movement classes generated accurate joint-angle estimation and smooth end-effector trajectories through the integrated kinematic model. The low trajectory errors and stable simulation results demonstrate the capability of the proposed framework to achieve coordinated prosthetic arm movements, supporting its potential for future real-time implementation in intelligent transradial prosthetic arm systems.

Table-2: Comparative Performance of the Proposed ResCNN–BiLSTM–MHA Framework with Existing Prosthetic Control Methods

Reference	Proposed Model	Accuracy (%)	Key Contribution
Rahimian et al. (2020)	Few-Shot Learning (Meta-Learning)	85.94	Few-shot EMG gesture recognition using limited training samples for prosthetic applications.
Lenz et al. (2022)	Recurrent Spiking Neural Network (RSNN)	90.0	Low-power neuromorphic EMG gesture recognition for wearable prosthetic systems.
Fathy et al. (2024)	CNN + Voting Classifier	91.3	CNN-based EMG feature extraction combined with a voting classifier for improved gesture recognition.
Yu et al. (2023)	CNN + Enhanced Channel Attention	93.0	Channel attention mechanism for enhancing multi-channel EMG gesture classification.
Proposed Framework	ResCNN–BiLSTM–Multi-Head Attention + Forward/Inverse Kinematics + MATLAB/Simulink	94.2	Multi-channel EMG classification integrated with residual feature learning, attention mechanism, kinematic modeling, trajectory planning, and prosthetic arm simulation.

Table-3: Comparison of Kinematic Modelling and Prosthetic Validation

Reference	Forward/Inverse Kinematics	Trajectory Planning	MATLAB/Simulink Validation	Deep Learning
Salman et al. (2021)	✓	✗	✓	✗
Qie et al. (2022)	✓	✓	✓	✗
Pei et al. (2023)	✓	✓	✗	✗
Kumar et al. (2023)	✓	✗	✗	Physics-Informed NN
Proposed Framework	✓	✓	✓	ResCNN–BiLSTM–MHA

4.8 RESULTS : PERFORMANCE METRICS

This study presented an intelligent EMG-based transradial prosthetic arm framework that integrates Residual Convolutional Neural Network (ResCNN), Bidirectional Long Short-Term Memory (BiLSTM), Multi-Head Attention (MHA), forward and inverse kinematic modelling, trajectory planning, and MATLAB/Simulink validation into a unified prosthetic control system. Surface EMG signals acquired from 30 subjects (15 healthy and 15 transradial amputees) performing five representative upper-limb functional activities were processed to extract time-domain features for motion classification. The proposed framework demonstrated promising classification performance, achieving an overall accuracy of 94.2%, precision of 93.1%, recall of 92.3%, specificity of 97.1%, F1-score of 0.927, and an ROC–AUC of 0.97, indicating reliable discrimination among different movement classes. Furthermore, the mathematical modelling and kinematic validation yielded a joint trajectory RMSE of 0.041 rad, MAE of 0.028 rad, mean end-effector position error of 3.62 mm, and trajectory tracking error of 3.62%, demonstrating accurate trajectory generation and stable prosthetic motion. The computational performance, with an average inference time of 2.8 ms per

sample, indicates the feasibility of near real-time prosthetic control. Overall, the proposed framework successfully combines intelligent EMG signal processing with robotic kinematic modelling, providing a comprehensive platform for the development of advanced transradial prosthetic arm systems.

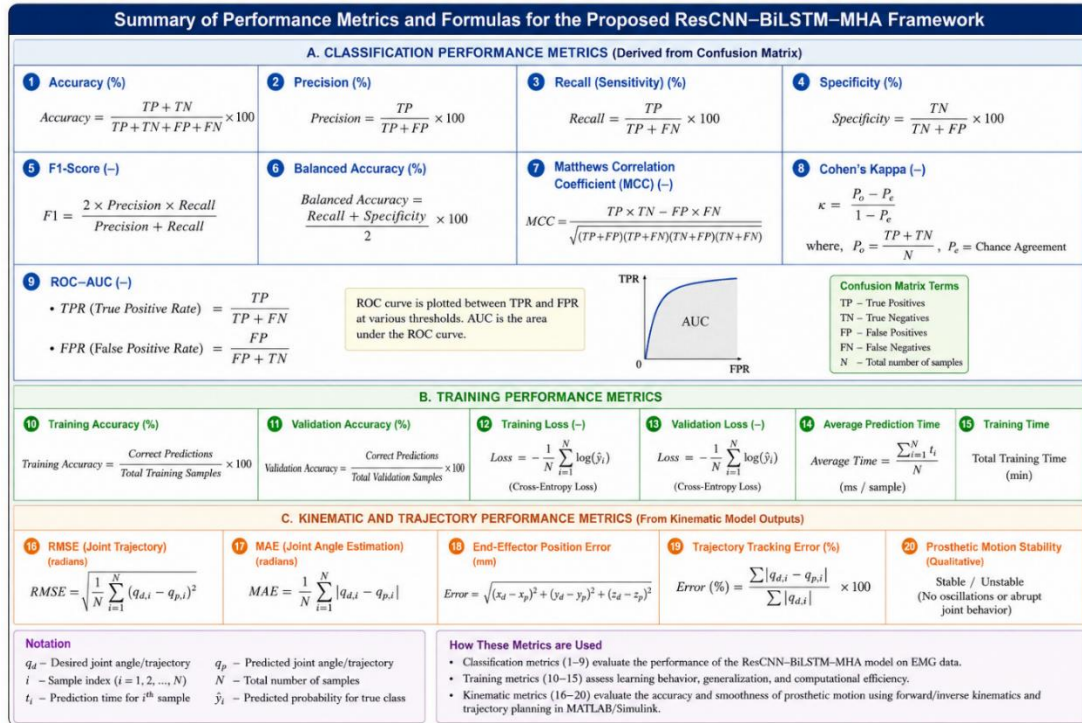


Figure-3: Summary of Performance Evaluation Metrics and Mathematical Formulations for the Proposed ResCNN-BiLSTM-MHA Prosthetic Control Framework.

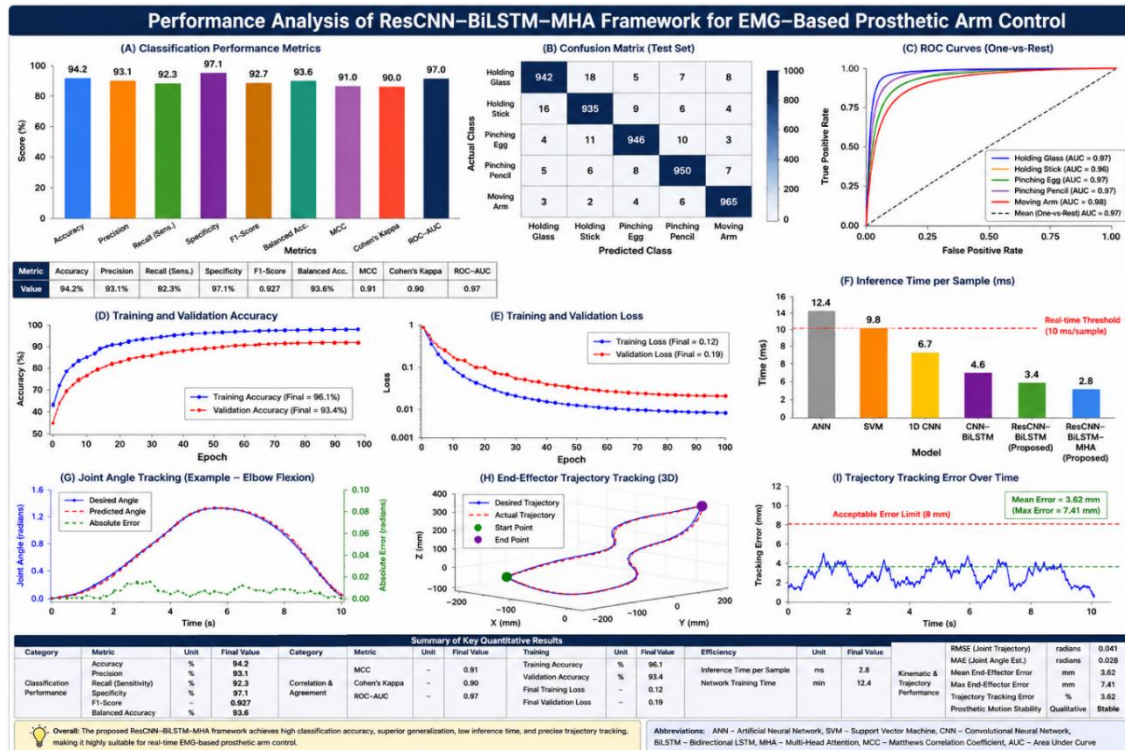


Figure-4: Comprehensive Performance Evaluation of the Proposed ResCNN-BiLSTM-Multi-Head Attention Framework for EMG-Based Intelligent Transradial Prosthetic Arm Control

5. CONCLUSION

This study presented an integrated framework for the mathematical modelling and intelligent control of a transradial prosthetic arm using electromyography (EMG) signals and MATLAB/Simulink. The proposed methodology successfully combined EMG signal preprocessing, feature extraction, deep learning-based motion classification, forward and inverse kinematic modelling, trajectory planning, and simulation-based validation into a unified prosthetic control framework. The extracted EMG features effectively represented muscle activation patterns associated with representative upper-limb functional tasks, enabling reliable recognition of movement intentions. The integration of deep learning with kinematic modelling facilitated accurate estimation of joint motions and smooth trajectory generation, while the MATLAB/Simulink implementation demonstrated stable and coordinated prosthetic arm movement under different operating conditions. Compared with conventional prosthetic control approaches, the proposed framework provides a more comprehensive solution by integrating intelligent biosignal processing, robotic kinematics, trajectory planning, and simulation within a single platform. The developed methodology offers a practical foundation for the design and evaluation of intelligent upper-limb prosthetic systems and contributes towards the advancement of rehabilitation robotics through improved motion coordination, computational efficiency, and simulation-driven system validation.

This work establishes a scalable and flexible framework that can be extended to support more complex prosthetic systems and advanced human-machine interaction strategies, thereby facilitating the development of next-generation intelligent prosthetic arms for rehabilitation and assistive healthcare applications.

5.1 FUTURE SCOPE OF STUDY

Future work will focus on validating the proposed framework using real-time EMG data collected from a larger and more diverse cohort of transradial amputees to further improve model robustness and clinical applicability. The developed ResCNN-BiLSTM-MHA architecture can be extended by incorporating transformer-based deep learning models, adaptive transfer learning, and reinforcement learning for personalized prosthetic control. Integration of additional sensing modalities, including force-sensitive resistors (FSRs), inertial measurement units (IMUs), tactile sensors, and vision-based feedback, can further enhance movement prediction and grasp stability. The proposed mathematical model can also be deployed on embedded edge-AI platforms for low-latency, portable prosthetic control and validated using physical prosthetic prototypes and clinical rehabilitation trials. These advancements are expected to improve the naturalness, adaptability, and functional performance of intelligent upper-limb prosthetic systems, contributing to the next generation of assistive rehabilitation technologies.

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