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A Comparative Study of Machine Learning and Deep Neural Architectures for EMG-Based Prosthetic Hand Gesture Recognition

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Abstract— Surface electromyography (sEMG) has emerged as a widely adopted non-invasive interface for prosthetic hand control due to its ability to capture muscle activation patterns associated with user intent. However, the inherent non-stationary nature of EMG signals, together with noise, motion artifacts and physiological variability, continues to present challenges for reliable gesture recognition. This study presents a comparative evaluation of classical machine learning and deep learning approaches for EMG-based prosthetic hand gesture recognition.EMG signals were acquired from forearm muscles using a BIOPAC Systems Inc. MP150 data acquisition system operating in a single-channel configuration with a sampling frequency of 400 Hz. The recorded signals were pre-processed using band-pass and notch filtering, followed by normalization and sliding-window segmentation. A unified experimental framework was established to ensure consistent evaluation across all investigated models. Classical machine learning classifiers, including Support Vector Machine (SVM) and Random Forest (RF), were compared with deep learning architectures comprising a Convolutional Neural Network (CNN) and a Temporal Convolutional Network (TCN).

Experimental results demonstrated successful classification of hand gestures across all evaluated models. The Random Forest and SVM classifiers achieved accuracies of 90.2% and 88.4%, while the CNN and TCN achieved accuracies of 94.1% and 95.8% respectively under the experimental conditions considered in this study. Among the investigated approaches, the TCN produced the highest overall performance, indicating the benefit of temporal modeling for EMG signal interpretation. The results further highlight the trade-off between classification accuracy and computational complexity, with classical machine learning methods offering lower implementation overhead and deep learning models providing superior recognition performance.The findings suggest that temporal deep learning architectures represent a promising direction for EMG-based prosthetic control systems. Future work will focus on lightweight deployment strategies, multimodal sensing integration and adaptive learning techniques to improve robustness in practical assistive applications.

Keywords— Surface electromyography (sEMG), prosthetic hand control, gesture recognition, machine learning, deep learning, convolutional neural network, temporal convolutional network, human–machine interaction.

I. INTRODUCTION

The loss of upper-limb functionality directly affects an individual's ability to perform daily activities, thereby reducing overall quality of life. Prosthetic hands provide an assistive solution by restoring motor capabilities in individuals with limb loss or neuromuscular impairments. Among the available control approaches, surface electromyography (sEMG) remains one of the most widely adopted techniques because it offers a non-invasive means of capturing the electrical activity generated by skeletal muscle contractions [1,2]. These signals contain information related to motor intent, making them suitable for intuitive control of prosthetic devices and other human–machine interface systems [3].EMG signals reflect underlying motor unit activation and provide valuable insight into muscle behavior during voluntary movement. This has enabled a wide range of applications, including prosthetic control, rehabilitation systems, exoskeletons and gesture-based interaction. However, the practical use of EMG signals remains challenging because of their non-stationary and noisy nature. Signal characteristics are influenced by factors such as electrode placement, motion artifacts, muscle fatigue and physiological variability, making reliable interpretation a complex signal processing and pattern recognition problem [4].

Over the past two decades, EMG-based prosthetic control systems have evolved alongside advances in signal processing, machine learning and embedded computing [5]. Early systems relied primarily on amplitude thresholding, where muscle activation triggered predefined prosthetic actions [6].

Although computationally efficient, these methods provided limited control functionality and required significant user adaptation. Subsequent developments introduced sequential control strategies based on multiple EMG channels and rule-switching mechanisms, improving functionality at the expense of intuitiveness and response speed [7].A significant advancement occurred with the adoption of pattern recognition techniques, where machine learning algorithms such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN) and Random Forest (RF) classifiers enabled direct classification of EMG patterns into multiple gesture classes [8-10]. These approaches improved both flexibility and usability in prosthetic control applications.

More recently, deep learning-based approaches have attracted considerable attention [11,12]. Architectures such as Convolutional Neural Networks (CNNs) and temporal neural models are capable of learning hierarchical representations directly from EMG data, reducing dependence on manual feature engineering [13,14]. By capturing both spatial and temporal characteristics of muscle activation patterns, these models have demonstrated improved classification performance and more natural control behavior.Despite these advances, practical deployment remains challenging. Deep learning models often achieve superior classification accuracy but require increased computational and memory resources, which can limit their deployment on embedded prosthetic platforms. Furthermore, EMG signal variability across recording sessions and operating conditions continues to affect reliability and classification performance [15,16]. Consequently, a balance must be achieved between classification accuracy, robustness and computational efficiency for practical real-time prosthetic control [17,18].

To address these challenges, this study presents a comparative evaluation of classical machine learning methods and deep neural architectures for EMG-based hand gesture recognition. EMG signals acquired from forearm muscles are processed through a structured pipeline involving preprocessing and segmentation prior to classification. Classical machine learning models, including Support Vector Machines and Random Forest classifiers, are evaluated alongside deep learning architectures such as Convolutional Neural Networks and Temporal Convolutional Networks (TCN). The comparison focuses on classification performance, temporal modeling capability and suitability for deployment in real-time embedded systems.

The contribution of this work lies in establishing a consistent evaluation framework for EMG signal classification while examining the trade-offs between model accuracy and computational requirements. Additionally, practical considerations associated with deploying these models on embedded and edge computing platforms are discussed, with emphasis on achieving reliable performance under resource constraints.

II. EMG SIGNAL PROCESSING

The interpretation of EMG signals for prosthetic hand gesture recognition requires a structured processing pipeline capable of converting raw muscle activity into reliable inputs for classification. Due to the non-stationary and noisy characteristics of EMG signals, several signal processing stages are required to improve signal quality and ensure consistent model performance [15,16]. In this study, the processing pipeline was designed with emphasis on computational efficiency and suitability for real-time prosthetic applications.

The complete workflow consists of signal acquisition, preprocessing and filtering, signal segmentation and gesture classification as shown in Figure 1. These stages collectively transform recorded muscle activity into meaningful representations that can be utilized by machine learning and deep learning models for gesture recognition.

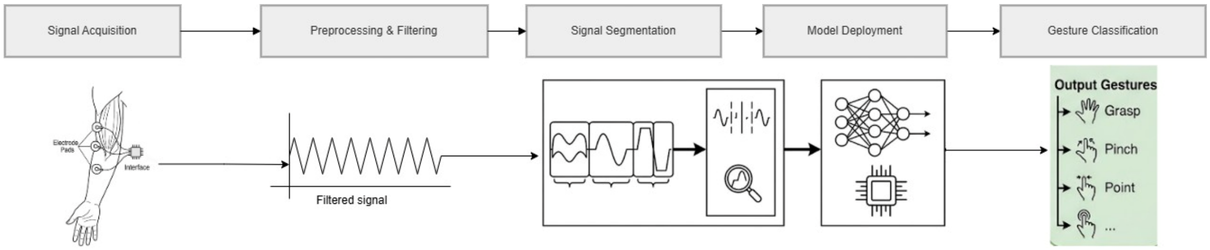


Figure 1: EMG workflow

A. Signal Acquisition and Preprocessing

EMG signals were acquired from forearm muscles using a BIOPAC Systems Inc. MP150 data acquisition system configured for single-channel recording. The acquisition setup was selected to investigate gesture recognition using a simplified and computationally efficient EMG recording configuration suitable for practical implementation.Signals were sampled at 400 Hz, providing sufficient temporal resolution to capture relevant muscle activation patterns while maintaining manageable computational requirements.

To improve signal quality, preprocessing operations including band-pass filtering, notch filtering and normalization were applied.
A 20–180 Hz band-pass filter was used to suppress motion artifacts and high-frequency noise while preserving the dominant frequency components of the acquired EMG signals. Power-line interference was reduced using a 50 Hz notch filter, with the filtering stage designed to accommodate common 50/60 Hz electrical interference encountered in practical acquisition environments. Signal normalization was subsequently performed to reduce amplitude variations and provide consistent input scaling for model training and evaluation.

B. Signal Segmentation

The EMG signals were segmented using a sliding-window approach with a window length of 200 samples and 50% overlap between consecutive windows. At a sampling frequency of 400 Hz, each segment corresponds to a temporal duration of 0.5 seconds, providing an effective balance between temporal resolution and signal stability.
The use of overlapping windows offers several advantages:

- Increases the number of available training samples
- Preserves temporal continuity between adjacent signal segments
- Improves classification robustness by reducing sensitivity to transition boundaries

This segmentation strategy supports near real-time operation while ensuring that each signal segment contains sufficient information to represent the underlying gesture activity.For the classical machine learning classifiers, descriptive time-domain features including Mean Absolute Value (MAV), Root Mean Square (RMS), Waveform Length (WL), Zero Crossing (ZC) and Variance (VAR) were extracted from each segmented EMG window. These features have been widely adopted in myoelectric control and pattern-recognition systems because of their effectiveness and computational simplicity [1], [13]. The resulting feature vectors were subsequently used for SVM and Random Forest classification, whereas CNN and TCN models operated directly on segmented EMG signals.

III. EXPERIMENTAL METHODOLOGY

A. Data Acquisition

Surface electromyography (sEMG) signals were acquired from the forearm muscles of a healthy participant using a BIOPAC Systems Inc. MP150 data acquisition system. Surface electrodes were positioned over forearm muscle groups associated with hand and finger movements to capture gesture-related muscle activity. A single-channel acquisition configuration was employed to investigate gesture recognition using a simplified EMG recording setup.Signals were sampled at 400 Hz, providing sufficient temporal resolution for capturing muscle activation dynamics while maintaining manageable computational requirements for subsequent processing and classification.
A total of four hand gesture classes were considered in this study. Multiple recording sessions were conducted under controlled laboratory conditions, resulting in approximately 43 minutes of EMG recordings. Following preprocessing and segmentation using a 200-sample sliding window with 50% overlap, a total of 2,800 labeled EMG segments were obtained for subsequent training and evaluation. Following manual removal of rest periods and unusable recordings, 2,800 gesture-related segments were retained for model training and evaluation. The resulting dataset was balanced across gesture classes to minimize class-specific bias during model training.
The present study was designed as a proof-of-concept investigation using recordings obtained from a single healthy participant. Consequently, the reported results should be interpreted as an evaluation of model behavior under controlled conditions rather than a subject-independent assessment. Investigation involving multiple participants and amputee subjects remains an important direction for future work.

B. Data Preparation and Labeling

The acquired EMG signals were processed using the signal processing pipeline described in Section 2. Following preprocessing and segmentation, each signal segment was assigned a label corresponding to the performed gesture.The resulting labeled segments were subsequently used for training and evaluating both classical machine learning and deep learning models. This approach ensured that all classification methods were evaluated using identical signal recordings and experimental conditions.

C. Training and Testing Strategy

The processed dataset was divided into training and testing subsets using an 80:20 split. The training subset was used for model development, while the testing subset provided an independent evaluation of classification performance on previously unseen signal segments.The distribution of gesture classes was maintained across both subsets to ensure a balanced and reliable performance assessment.To minimize information leakage between training and testing data, the dataset was partitioned at the trial level prior to model training. Signal segments originating from a given recording trial were assigned exclusively to either the training or testing subset. This procedure prevents overlapping windows from appearing simultaneously in both datasets and provides a more reliable estimate of classification performance.

D. Model Training Configuration

All models were trained under consistent experimental conditions to enable fair comparison.

For deep learning architectures (CNN and TCN):

- Optimizer: Adam
- Batch Size: 32
- Number of Epochs: 50
- Loss Function: Categorical Cross-Entropy

For classical machine learning models (SVM and Random Forest), standard implementations with baseline parameter settings were adopted without extensive hyperparameter optimization. This approach allows comparison of model architectures while minimizing the influence of model-specific tuning.

All experiments were implemented using Python-based frameworks, including Scikit-learn for machine learning models and TensorFlow/Keras for deep learning architectures.

E. Evaluation Metrics

Model performance was evaluated using confusion matrix components, where true positives (TP) correspond to correctly classified gesture segments, true negatives (TN) represent correctly rejected non-target gestures, false positives (FP) indicate incorrect activations and false negatives (FN) denote missed gesture detections.

Accuracy provides an overall measure of classification performance by indicating the proportion of correctly classified EMG segments across all gesture classes:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \qquad \ldots(1)$$

Precision reflects the reliability of predicted gestures and indicates how frequently a detected gesture corresponds to the intended action:

$$Precision = \frac{TP}{TP + FP} \qquad \ldots(2)$$

Recall measures the ability of the model to correctly identify intended gestures from the EMG signals:

$$Recall = \frac{TP}{TP + FN} \qquad \ldots(3)$$

The F1-score combines precision and recall into a single metric, providing a balanced assessment of classification performance:

$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \qquad \ldots(4)$$

Together, these metrics provide insight into both classification accuracy and system reliability, which are critical considerations in EMG-based prosthetic control systems.Since gesture recognition represents a multi-class classification problem, precision, recall and F1-score were computed using macro-averaged measures across all gesture classes. This approach ensures that each gesture class contributes equally to the reported performance metrics regardless of class frequency.

F. Experimental Setup and Visualization

Surface electrodes were positioned over the forearm muscles responsible for hand and finger movements to capture gesture-related EMG activity. The BIOPAC MP150 acquisition system was used to record the signals under controlled laboratory conditions. The recorded data were subsequently processed using the acquisition and preprocessing pipeline described in Section 2.

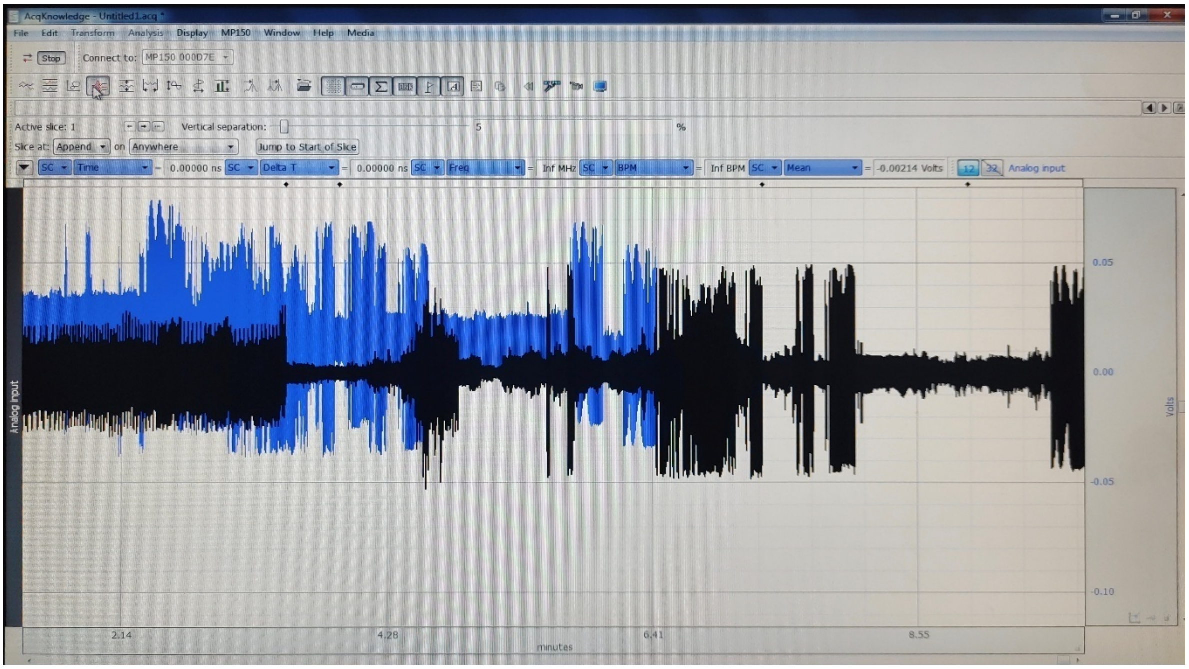
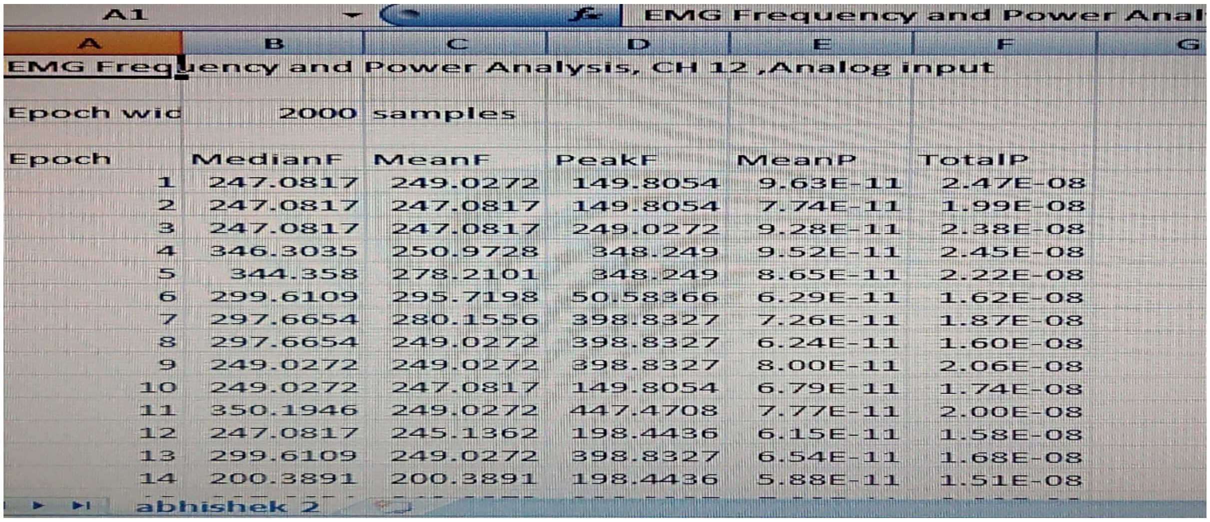


Figure 2: Recorded EMG signals from forearm muscles during gesture activity.

Figure 2 presents representative EMG signals recorded during gesture execution together with their corresponding frequency-domain representations. The time-domain signals exhibit clear amplitude variations associated with different muscle activation patterns. In the frequency domain, the dominant signal components are concentrated within the 20–180 Hz range, consistent with the applied filtering strategy. These observations indicate that the preprocessing stages effectively preserved relevant EMG information while reducing noise and interference.



EMG Frequency and Power Analysis, CH 12 ,Analog input

Epoch wid 2000 samples

Epoch	MedianF	MeanF	PeakF	MeanP	TotalP
1	247.0817	249.0272	149.8054	9.63E-11	2.47E-08
2	247.0817	247.0817	149.8054	7.74E-11	1.99E-08
3	247.0817	247.0817	249.0272	9.28E-11	2.38E-08
4	346.3035	250.9728	348.249	9.52E-11	2.45E-08
5	344.358	278.2101	348.249	8.65E-11	2.22E-08
6	299.6109	295.7198	50.58366	6.29E-11	1.62E-08
7	297.6654	280.1556	398.8327	7.26E-11	1.87E-08
8	297.6654	249.0272	398.8327	6.24E-11	1.60E-08
9	249.0272	249.0272	398.8327	8.00E-11	2.06E-08
10	249.0272	247.0817	149.8054	6.79E-11	1.74E-08
11	350.1946	249.0272	447.4708	7.77E-11	2.00E-08
12	247.0817	245.1362	198.4436	6.15E-11	1.58E-08
13	299.6109	249.0272	398.8327	6.54E-11	1.68E-08
14	200.3891	200.3891	198.4436	5.88E-11	1.51E-08

Figure 3 : Extracted feature distributions for classification.

Figure 3 illustrates representative distributions of extracted time-domain features including MAV, RMS, WL, ZC and VAR obtained from segmented EMG recordings.

Observable variations between gesture classes demonstrate the presence of discriminative information within the acquired signals, supporting their suitability for machine learning and deep learning-based classification.Collectively, these visualizations validate the signal acquisition and processing pipeline and provide qualitative support for the reported classification results.

IV. MACHINE LEARNING MODELS

To evaluate conventional approaches for EMG gesture recognition, classical machine learning models were trained using descriptive signal characteristics derived from the segmented EMG recordings. While deep learning architectures operate directly on segmented EMG signals, classical classifiers require a compact representation of the underlying muscle activity.

For this purpose, each segmented EMG window was represented using commonly adopted time-domain descriptors, including Mean Absolute Value (MAV), Root Mean Square (RMS), Waveform Length (WL), Zero Crossing (ZC) and Variance (VAR). These measures provide a concise representation of signal amplitude, variability and activation characteristics while maintaining computational efficiency suitable for real-time implementation.

A. Support Vector Machine (SVM)

The Support Vector Machine (SVM) classifier was employed to learn decision boundaries between gesture classes within a high-dimensional feature space. To account for the nonlinear nature of EMG signals, a Radial Basis Function (RBF) kernel was utilized to model complex relationships between feature vectors. Prior to training, feature values were standardized to ensure uniform scaling across all dimensions.

By maximizing the separation margin between classes, the SVM provides robust classification performance and has been widely adopted in EMG-based gesture recognition applications. Its ability to handle nonlinear decision boundaries makes it particularly suitable for distinguishing subtle differences in muscle activation patterns.

B. Random Forest (RF)

The Random Forest (RF) classifier was employed as an ensemble learning approach consisting of multiple decision trees trained on different subsets of the data. Final predictions were determined through majority voting across the ensemble.

This approach improves classification stability, reduces sensitivity to noise and mitigates overfitting. These characteristics are particularly advantageous for EMG signals, which are often affected by variations in electrode placement, muscle fatigue and recording conditions. Additionally, Random Forest models provide efficient training and inference while maintaining competitive classification performance.

C. Implementation Consistency

Both classical machine learning models were trained using identical signal segments and equivalent feature representations to ensure a fair comparison. Hyperparameter tuning was intentionally limited, allowing the models to serve as baseline benchmarks against the deep learning architectures evaluated in this study.

The resulting performance therefore reflects the inherent capabilities of the classification approaches rather than extensive model-specific optimization.

V. DEEP LEARNING ARCHITECTURES

Deep learning models were employed to learn discriminative representations directly from segmented EMG signals, eliminating the need for extensive manual feature engineering. Unlike classical machine learning approaches, these models operate directly on preprocessed EMG segments and automatically learn relevant patterns associated with different gestures.

The deep learning component of this study consists of a Convolutional Neural Network (CNN) and a Temporal Convolutional Network (TCN). Both architectures were evaluated using identical signal recordings and training conditions to enable a consistent comparison with the classical machine learning models.

The Temporal Convolutional Network (TCN) was selected because EMG signals exhibit temporal dependencies and TCN provides larger receptive fields through dilated convolutions while maintaining lower computational complexity than recurrent architectures. This makes TCN particularly suitable for modeling sequential muscle activation patterns in real-time prosthetic control applications.

A. Convolutional Neural Network (CNN)

The Convolutional Neural Network (CNN) was designed to automatically learn local patterns from segmented EMG signals. The network receives input segments of size (200 × 1), where 200 represents the temporal samples contained within each EMG window and 1 corresponds to the single acquisition channel.

The CNN architecture consisted of two one-dimensional convolutional layers with 32 and 64 filters respectively, each followed by batch normalization, ReLU activation and max-pooling operations. The extracted feature maps were flattened and passed through a dense layer of 128 neurons before final softmax classification.By learning directly from segmented EMG signals, the CNN is capable of identifying discriminative local activation patterns associated with different hand gestures.

B. Temporal Convolutional Network (TCN)

The Temporal Convolutional Network (TCN) was employed to model temporal relationships within EMG sequences. Unlike conventional convolutional networks, the TCN utilizes causal and dilated convolutions, enabling the network to capture temporal dependencies while preserving the sequential structure of the signal [19].

The model receives segmented EMG inputs of length 200 samples and consists of stacked dilated convolutional layers with progressively increasing dilation factors. This design expands the receptive field of the network without a substantial increase in computational complexity, allowing both short-term and long-term temporal information to be incorporated into the classification process.The TCN architecture consisted of stacked dilated convolutional layers employing dilation factors of 1, 2, 4 and 8. Each layer utilized 64 convolutional filters followed by nonlinear activation and normalization. A global average pooling layer aggregated temporal representations prior to final classification through a softmax output layer.

A global pooling layer aggregates the learned temporal features, which are subsequently passed to a fully connected layer with softmax activation for gesture classification. The architecture is therefore capable of modeling sequential muscle activation patterns that may extend across multiple time samples.

Additionally, TCN has the potential to support efficient inference due to its convolutional structure while preserving the ability to model long-range temporal dependencies. These characteristics make it a promising candidate for future embedded prosthetic control systems.

C. Training Consistency

Both deep learning models were trained using the same segmented EMG recordings and identical training configurations described in Section 3. This ensures that performance differences primarily reflect architectural characteristics rather than variations in training procedures.By learning directly from segmented EMG signals, the CNN and TCN architectures provide an end-to-end classification framework capable of automatically discovering relevant representations for gesture recognition.

VI. RESULTS AND DISCUSSION

A. Quantitative Performance Evaluation

The performance of the evaluated classification models is summarized in Table 1.

Table 1 : Performance of models

Model	Accuracy	Precision	Recall	F1 Score
SVM	88.4%	0.87	0.86	0.86
Random Forest	90.2%	0.89	0.88	0.88
CNN	94.1%	0.93	0.92	0.92
TCN	95.8%	0.95	0.94	0.94

The experimental results demonstrate successful classification of hand gestures using both classical machine learning and deep learning approaches. Among the evaluated models, the Temporal Convolutional Network (TCN) achieved the highest classification accuracy of 95.8%, followed by the Convolutional Neural Network (CNN) with an accuracy of 94.1%. The classical machine learning models also achieved competitive performance, with Random Forest and Support Vector Machine classifiers reaching accuracies of 90.2% and 88.4%, respectively.

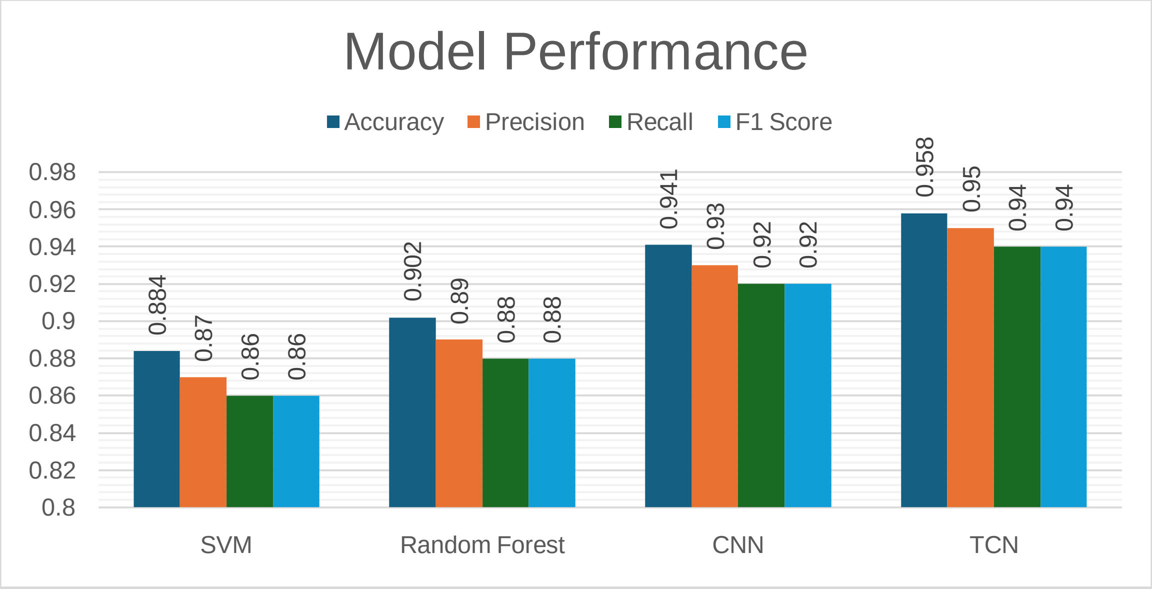


Figure 4: Comparative performance of SVM, Random Forest, CNN and TCN models based on classification accuracy.

Figure 4 presents a comparative visualization of the performance metrics obtained by the evaluated models. Consistent improvements can be observed from classical machine learning approaches to deep learning architectures across all evaluation measures. While the Support Vector Machine and Random Forest classifiers achieved competitive performance, the CNN and TCN models consistently produced higher accuracy, precision, recall and F1-score values. Among all evaluated methods, the TCN demonstrated the strongest overall performance, indicating the effectiveness of temporal feature learning for EMG-based gesture recognition. The relatively small differences between precision, recall and F1-score values further suggest balanced classification behavior across the evaluated gesture classes.The reported performance values correspond to the testing subset under the experimental configuration described in Section 3. Future studies may incorporate repeated trials, cross-validation and statistical significance testing to further assess model robustness.For multiclass evaluation, TP, TN, FP and FN were computed using a one-versus-rest formulation for each gesture class prior to macro-averaging.

Across all evaluation metrics, the deep learning models produced higher scores than the classical approaches under the experimental conditions considered in this study. The consistent improvements observed in accuracy, precision, recall and F1-score indicate that deep architectures were able to capture discriminative gesture-related information more effectively from the recorded EMG signals.

B. Comparison Between Classical and Deep Learning Approaches

The classical machine learning models achieved reliable classification performance while maintaining relatively simple model structures. Their use of compact time-domain descriptors enabled efficient learning and produced satisfactory gesture recognition accuracy.In contrast, the deep learning architectures operated directly on segmented EMG recordings and learned task-specific representations automatically during training. This capability allows the models to capture complex signal relationships that may not be fully represented by handcrafted descriptors alone. Under the acquisition conditions used in this study, the CNN and TCN models achieved performance improvements of approximately 4–7% over the classical approaches.These findings suggest that end-to-end learning approaches can provide additional discriminative capability when sufficient training data are available, while classical machine learning methods remain attractive for applications requiring lower computational complexity.

C. CNN vs. TCN: Temporal Modeling Analysis

Both deep learning architectures achieved high classification performance; however, the TCN consistently produced the best results across all evaluation metrics. The CNN effectively learned local signal patterns associated with different gestures through convolutional feature extraction, resulting in strong classification performance.The TCN further improved performance by incorporating dilated temporal convolutions that allow information to be aggregated across a wider temporal context.

Since EMG signals represent time-varying muscle activation patterns, the ability to model temporal relationships appears beneficial for gesture recognition. The superior performance of the TCN suggests that temporal dependencies contained within the recorded EMG signals contributed useful information for classification.

While the numerical performance difference between CNN and TCN is relatively modest, the results indicate that temporal modeling can provide measurable improvements in classification accuracy within the experimental setup considered in this work.

D. Feature-Based vs. End-to-End Learning

The results highlight the trade-off between feature-based and end-to-end learning approaches. Classical machine learning models utilize manually derived signal descriptors that provide a compact and computationally efficient representation of EMG activity. These methods offer simpler implementation and reduced computational requirements while still achieving competitive performance.In contrast, CNN and TCN architectures learn representations directly from segmented EMG signals without requiring extensive manual feature engineering. This enables automatic extraction of discriminative patterns and nonlinear relationships that may be difficult to capture using predefined descriptors.The improved performance observed for the deep learning models indicates the benefits of learned representations; however, these gains are typically accompanied by increased training complexity and greater computational requirements. Consequently, model selection should consider both classification performance and available computational resources.

E. Implications for Real-Time Prosthetic Control

For practical prosthetic control systems, classification accuracy must be balanced against computational efficiency and implementation complexity. The classical machine learning models evaluated in this study provide strong performance with comparatively low computational requirements, making them suitable candidates for resource-constrained environments.The CNN achieved a favorable balance between classification accuracy and model complexity, demonstrating that deep learning can improve recognition performance while maintaining a relatively straightforward architecture.The TCN achieved the highest classification accuracy by effectively modeling temporal relationships within the EMG signals. Furthermore, TCN has the potential to support efficient inference due to its convolutional structure while preserving the ability to model long-range temporal dependencies. These characteristics make it a promising architecture for future real-time prosthetic control applications.Although deployment-related metrics such as latency, memory consumption and energy usage were not explicitly evaluated in this study, the observed classification performance suggests that deep temporal architectures warrant further investigation for embedded prosthetic systems.

F. Key Observations

Several important observations emerge from the experimental results.First, all evaluated models successfully classified hand gestures from the recorded EMG signals, demonstrating the effectiveness of the proposed signal acquisition and processing pipeline.Second, deep learning architectures consistently achieved higher classification performance than the classical machine learning models under the experimental conditions considered in this study.Third, temporal modeling appears to play an important role in EMG-based gesture recognition, as evidenced by the superior performance of the Temporal Convolutional Network.Finally, the results indicate that both classical and deep learning approaches remain viable options for prosthetic control applications, with the choice of model depending on the desired balance between classification performance, computational complexity and deployment constraints.The classification accuracies obtained in this study are generally consistent with performance ranges reported in previous EMG gesture recognition literature employing machine learning and deep learning approaches. Direct comparison should be interpreted cautiously because differences in acquisition hardware, gesture sets, participant populations and evaluation protocols can substantially influence reported results.It should be noted that the results were obtained using recordings acquired under controlled experimental conditions. Additional investigation involving larger and more diverse datasets would be valuable for assessing performance across a broader range of operating conditions and users.

VII. FUTURE DIRECTIONS

The deployment of EMG-based gesture recognition systems on embedded prosthetic platforms requires careful consideration of both classification performance and computational efficiency. While deep learning architectures demonstrated superior classification performance in this study, they generally require greater computational resources and memory compared to conventional machine learning approaches.

This can present challenges when implementing such models on wearable or battery-powered prosthetic devices with limited hardware capabilities.

In contrast, classical machine learning models such as Support Vector Machines and Random Forest classifiers offer lower computational complexity and can be deployed more readily on resource-constrained platforms. However, this reduction in computational cost is often accompanied by lower classification performance. Consequently, practical prosthetic systems must balance recognition accuracy, inference speed, memory consumption and energy efficiency.Several challenges continue to affect the deployment of EMG-driven prosthetic control systems in real-world environments. Variability in muscle activation patterns, changes in electrode positioning and muscle fatigue can significantly alter EMG signal characteristics over time. These factors may reduce classification reliability and necessitate periodic recalibration. Additionally, embedded platforms often impose constraints on model size and computational complexity, limiting the deployment of advanced deep learning architectures without further optimization.

Techniques such as model quantization, pruning and lightweight network design offer potential solutions for reducing computational requirements while maintaining acceptable classification performance. Furthermore, the integration of efficient signal processing pipelines with compact deep learning architectures may provide a practical pathway toward real-time embedded deployment.Future research may focus on transfer learning for subject-independent recognition, integration of multimodal sensing modalities such as IMU and force sensors, lightweight temporal architectures for embedded deployment and adaptive online learning mechanisms capable of compensating for signal variability during long-term use.

Overall, continued progress in EMG-based prosthetic control will depend on the development of classification frameworks that achieve a balance between recognition performance, robustness and computational efficiency while remaining suitable for deployment in practical assistive devices.

VIII. CONCLUSION

This study presented a comparative evaluation of classical machine learning approaches and deep neural architectures for EMG-based hand gesture recognition. A unified processing framework incorporating signal acquisition, preprocessing, segmentation and classification was employed to ensure a consistent evaluation of the investigated models. Handcrafted time-domain descriptors were utilized for the classical machine learning classifiers, whereas the deep learning architectures operated directly on segmented EMG signals.

Experimental results obtained from forearm EMG recordings demonstrated that all evaluated models were capable of successfully classifying hand gestures. Among the investigated approaches, the Temporal Convolutional Network achieved the highest classification accuracy, followed closely by the Convolutional Neural Network. The observed performance improvements suggest that temporal modeling can provide additional discriminative capability for EMG-based gesture recognition by capturing sequential characteristics present within muscle activation patterns.The classical machine learning models achieved competitive performance while maintaining lower computational complexity, highlighting their continued relevance for resource-constrained applications. In contrast, the deep learning models achieved superior classification accuracy at the cost of increased computational requirements. These findings emphasize the trade-off between recognition performance and deployment complexity that must be considered when designing practical prosthetic control systems.

The results presented in this work were obtained under controlled experimental conditions and demonstrate the feasibility of both classical and deep learning approaches for EMG-based gesture classification. While the Temporal Convolutional Network produced the strongest overall performance within the evaluated experimental setup, further investigation involving larger and more diverse datasets would be valuable for assessing robustness across broader operating conditions.

In conclusion, temporal deep learning architectures represent a promising direction for EMG-driven prosthetic control. Future developments incorporating model optimization, adaptive learning strategies and multimodal sensing may further enhance the reliability, efficiency and practical usability of intelligent prosthetic systems.

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