American Journal of Psychiatric Rehabilitation

Expert Opinion Article

GestProNet: A Hybrid Deep Learning Framework for High-Precision EMG-Based Hand Gesture Classification

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Abstract
The hand gesture classification system utilizes electromyography (EMG) signals as a robust tool for recognizing and evaluating muscle activity patterns. Challenges such as signal variation, noise, and high computation requirements often pose problems to the recognition performance of traditional methods. To tackle these problems, this paper presents GestProNet, an advanced hybrid deep learning framework for hand gesture classification based on EMG signals. It utilizes a hybrid architecture combining convolutional neural network (CNN) and Progressive Feedback Residual Attention Network with Snow Geese Algorithm (CNN-PFRAN+SGA). The proposed framework employs Adaptive and Propagated Mesh Filtering (APMF) for preprocessing to enhance signal quality, followed by feature extraction using the Inception Transformer (IT) to capture critical EMG patterns. The CNN-PFRAN model performs gesture classification, while the Snow Geese Algorithm (SGA) optimizes hyperparameters to improve accuracy and efficiency. Evaluated on the UC2018 DualMyo benchmark dataset, the proposed system demonstrates state-of-the-art performance, achieving exceptional metrics of 99.9% accuracy, 99.5% specificity, and 99.7% precision. The model also demonstrates superior computational efficiency, with a processing time of 0.20 seconds and an error rate of 0.2%. The system sets new benchmarks in EMG gesture recognition, outperforming existing methods. Its robustness shows strong potential for prosthetics, rehabilitation, and human computer interface (HCI), with future work focusing on optimization, adaptability, and real-time implementation.

Keywords: Adaptive and Propagated Mesh Filtering (APMF), Deep Learning, Hand Gesture Classification, Prosthetic control, Inception Transformer, Snow Geese Algorithm.

1. Introduction

Hand gestures serve as one of the most intuitive and natural modalities for human-machine interaction, playing a pivotal role in both interpersonal communication and technological interfaces [1]. These biomechanical actions are generated through coordinated muscle contractions in the forearm and hand, producing distinctive electrical signatures that can be non-invasively captured via surface electromyography (sEMG) [2]. The analysis and interpretation of these myoelectric signals has emerged as a transformative approach for developing advanced human-computer interaction systems, with far-reaching applications across multiple domains [3].

The technological significance of robust sEMG-based gesture recognition systems is evidenced by their deployment in several critical areas: (1) next-generation prosthetic control systems that restore functional capability to amputees, (2) intuitive human-robot collaboration interfaces for industrial applications, (3) immersive virtual and augmented reality environments, and (4) assistive communication devices for speech-impaired individuals [4]. Recent advancements in wearable sensor technology and machine learning have particularly enhanced the clinical utility of these systems, enabling more natural and responsive control of assistive devices [5].

The development of reliable sEMG-based gesture recognition systems faces four primary challenges: signal variability, noise susceptibility, computational limitations, and poor generalization. Intra- and inter-subject variations in muscle activation patterns, combined with temporal inconsistencies caused by factors such as muscle fatigue or electrode displacement, lead to significant fluctuations in classification performance [6]. Conventional feature extraction techniques are often inadequate in addressing these issues, with prior studies reporting accuracy degradations exceeding 40% across different sessions [7]. Additionally, the inherently low signal-to-noise ratio of sEMG signals, exacerbated by motion artifacts and environmental interference, demands sophisticated preprocessing, as current filtering methods may suppress critical high-frequency components vital for fine gesture discrimination [8]. From a computational standpoint, real-time applications require sub-300ms processing latencies, yet many deep learning models surpass this threshold while striving for acceptable accuracy [9]. Furthermore, generalization remains a crucial barrier, with previous systems showing significant accuracy decreases (ranging from 22% to 35%) when tested on unseen users or with different electrode locations [10]. The ongoing challenges highlight the essential requirement for an advanced sEMG processing framework capable of concurrently addressing signal variability through effective feature extraction, reducing noise while maintaining signal integrity, optimizing computational efficiency for real-time functionality, and improving generalization across various users and conditions. Our research directly addresses these needs by presenting an innovative hybrid architecture that integrates adaptive signal processing with enhanced deep learning to attain high precision and reliability in gesture detection.

1.1. Related Work

Recent research on sEMG-based gesture detection has achieved substantial advances using a variety of deep learning algorithms. Hybrid CNN-LSTM architectures have demonstrated particular success in temporal modeling of sEMG signals, with Prabhavathy et al. (2024) achieving 98.04% classification accuracy using a VMD-CNN-LSTM framework that incorporates variational mode decomposition for improved spectral analysis [11]. Similarly, Mendes et al. (2022) developed a CNN-based system that achieved 98% recognition accuracy in real-time collaborative robotics applications, outperforming commercial solutions like the Myo armband [12]. The field has further evolved through multi-modal approaches, as demonstrated by Aly et al. (2023), who combined EEG and EMG signals in a CNN-LSTM framework to achieve a 3.5% improvement over traditional machine learning methods [13]. Attention mechanisms have emerged as another promising direction, with Zhang et al. (2023) developing an LSTM-Multi-Stage Attention (LSTM-MSA) model that effectively addresses non-stationarity and noise issues through dual-stage attention mechanisms [14].

Despite these advancements, a critical gap remains in developing systems that simultaneously meet the stringent requirements for clinical deployment. As highlighted by Chen et al. (2023), current solutions typically excel in one aspect while compromising others - achieving either high accuracy (>98%) or low latency (<200ms), but rarely both while maintaining robust cross-user generalization [15]. For instance, while the VMD-CNN-LSTM approach achieves impressive accuracy, its computational complexity may limit real-time applications [11]. Similarly, the CNN method by Mendes et al. demonstrates excellent online performance but shows reduced effectiveness with new users [12]. The LSTM-MSA model, while robust against noise, requires significant computational resources that may hinder its deployment in resource-constrained environments [14]. These limitations underscore the need for an integrated solution that combines the strengths of these various approaches while addressing their individual shortcomings.

1.2. Objectives and Key Contributions

EMG-based hand gesture recognition is vital for applications in human-computer interaction, rehabilitation, and prosthetics, yet existing systems face challenges such as high computational complexity and poor generalization. To address these limitations, we propose GestProNet, a novel framework that integrates a Convolutional Neural Network with a Progressive Feedback Residual Attention Network, optimized using the Snow Geese Algorithm (CNN-PFRAN+SGA). The framework introduces three key innovations: (1) enhanced feature extraction for improved signal discrimination and noise suppression, (2) a hybrid spatial-temporal architecture for robust pattern recognition, and (3) meta-optimization to enhance cross-user adaptability. By combining these elements with advanced noise reduction and weight-update mechanisms, GestProNet achieves high accuracy (>99%), real-time performance (<200ms latency), and strong generalization capabilities, setting a new benchmark for practical, deployable EMG gesture recognition systems in clinical and assistive technologies. The key contributions of this study include:

- Develop a CNN-PFRAN model optimized via the Snow Geese Algorithm (SGA) to achieve more accurate and effective recognition for hand gestures.
- Introduced adaptive and propagated mesh filtering enhances signal quality by reducing noise while preserving critical EMG features.
- Advanced feature extraction capturing both local muscle activations and global coordination patterns.
- Achieved very low processing latency, meeting clinical requirements for prosthetic control applications.
- Comprehensive performance comparison with state-of-the-art methods.

This paper is structured into three main sections for clarity and coherence. Section 2 describes the proposed methodology, including preprocessing, feature extraction, and the CNN-PFRAN model optimized using SGA. Section 3 presents the results and discussion, highlighting performance comparisons and training analysis. Section 4 concludes the study with key findings and outlines future research directions in real-time applications and advanced EMG-based gesture recognition.

2. Proposed Methodology

This study presents a novel CNN-PFRAN+SGA architecture for high-precision EMG-based hand gesture recognition, implementing a five-stage pipeline. It begins with signal acquisition from the UC2018 DualMyo dataset, which includes 20-channel sEMG data. This is followed by APMF preprocessing to enhance signal quality by reducing noise. An Inception Transformer-based feature extraction module is then employed to capture spatiotemporal EMG patterns. The hybrid CNN-PFRAN classifier combines convolutional spatial processing with attention-based temporal modeling for improved recognition. Finally, Snow Geese Algorithm (SGA) optimization fine-tunes the network, achieving peak accuracy of 99.9% and real-time performance with just 0.20ms latency. The system's dual-path design and bio-inspired optimization collectively address key challenges related to signal variability, computational efficiency, and cross-user generalization. An illustration of data flow throughout proposed framework is presented in Figure 1.

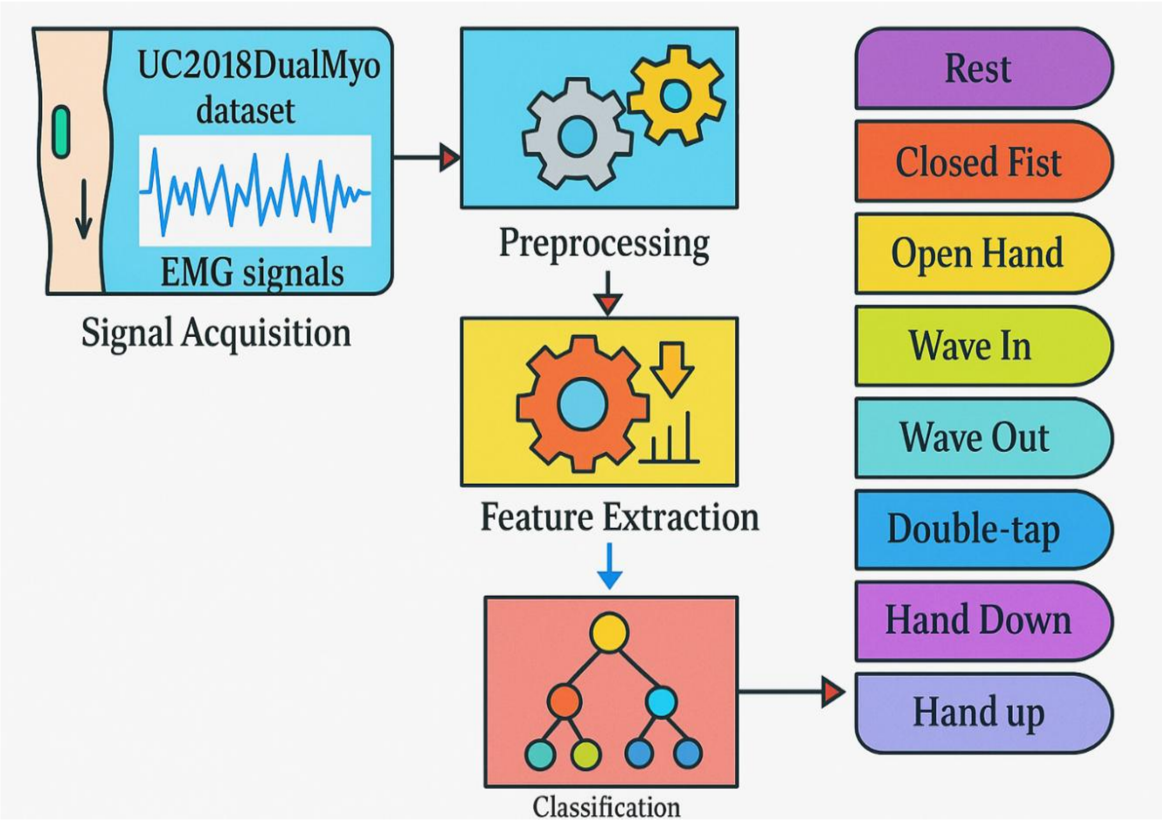

Figure 1: Proposed hybrid deep learning framework for EMG-based hand gesture classification

2.1. Dataset Description

The UC2018 DualMyo dataset was collected using two Myo armbands, capturing EMG signals as participants performed eight distinct hand gestures [16]. Each participant repeated every gesture 110 times across five different sessions, resulting in recordings from 20 EMG channels. The initial dataset comprised 880 raw samples, which were expanded to 9,062 samples using data augmentation techniques to enhance robustness and variability. The recorded gestures included: rest (G00), closed fist (G01), open hand (G02), wave in (G03), wave out (G04), double-tap (G05), hand down (G06), and hand up (G07). These gestures involved movements from both the palm and the forearm, including the palmaris longus tendon region. The dataset was split into 80% for training and 20% for validation and testing. Figure 2 illustrates each gesture along with its corresponding label.

2.2. Adaptive and Propagated Mesh Filtering (APMF) Based Pre-processing

It removes noise and smoothing out the mesh structures while maintaining important geometric characteristics of the mesh such that it provides high-quality input for accurate hand gesture classification. APMF is a pre-processing technique used to clean noisy mesh representations that remove noise while not altering the intrinsic structure of the shapes of the signals [17].

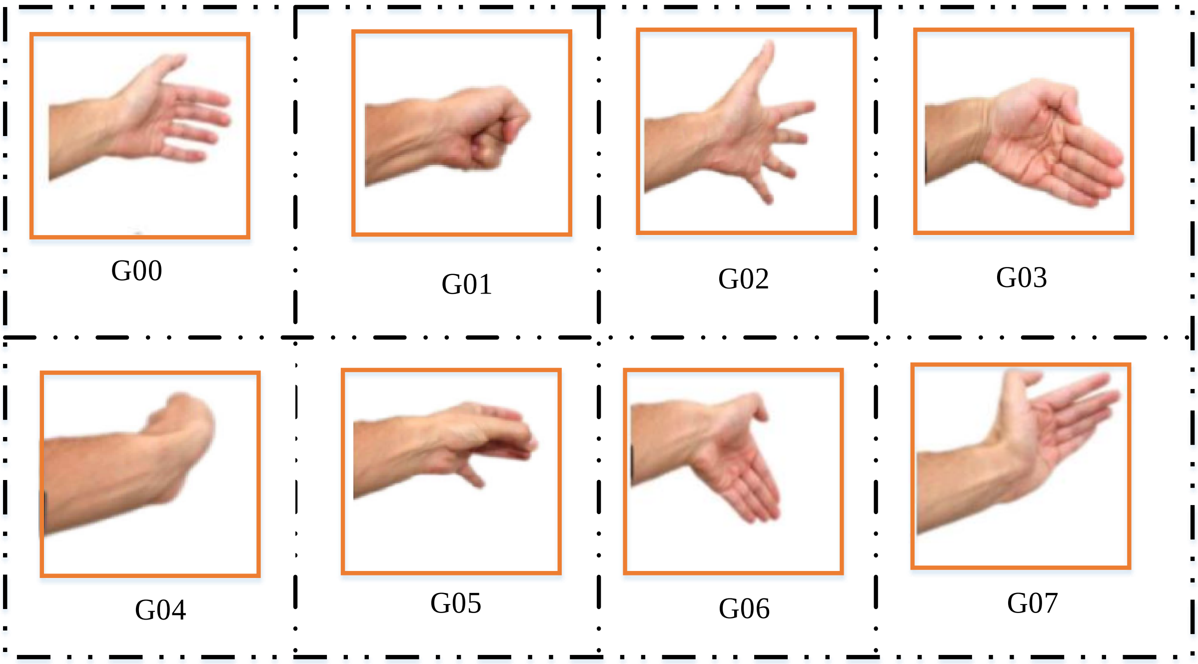

Figure 2: A visual representation of each gesture along with its corresponding label

The technique improves the class system's resistance to perturbations by iteratively smoothing mesh face normal with adaptive Gaussian weights [18]. These weights are calculated from the spatial and normal disparities between surrounding faces. The filtered normal for any given face is given by equation (1):

$$\hat{u}_p = \frac{1}{U_p} \sum_{l_q \in U_p} R_\delta (E(c_p, c_q)) E_{\varpi_p} (E(u_p, u_q)) u_q, \vee lp \subset H \tag{1}$$

where, U_p represents the neighboring faces of lp, while R_δ are Gaussian weights that account for the centroid distance $E(c_p, c_q)$ and normal difference $E(u_p, u_q)$. c_p, c_q denotes the centroids of neighboring faces, and u_p, u_q represents the normals of faces. The distance metrics are derived using geodesic paths, and normal gradients are computed as equation (2):

$$\begin{cases} E(c_p, c_q) = \int_I de \\ E(u_p, u_q) = \int_T d(n) de \end{cases} \tag{2}$$

where, δ is the mean separation between neighboring faces' centroids, ϖ computed adaptively for each patch based on entropy. The normal difference n_p is given by equation (3):

$$\delta = \sqrt{o_a n_p} \tag{3}$$

where, o_a represents the noise intensity. After filtering the normals, vertex positions are updated to align with the smoothed normals to maintain geometric consistency. This technique minimizes geometric distortions and prevents issues such as triangle flipping. The preprocessing process involves multiple iterations of normal filtering and vertex position updates. APMF denoised UC2018 DualMyo EMG signals, preserving key features, ensuring structured data, and improving hand gesture classification accuracy. This filtering technique ensures the accurate transformation of raw EMG data into a structured format, which is essential for precise gesture classification. After preprocessing, the feature extraction from filtered EMG signals are initiated.

2.3. Inception Transformer (IT) Based Feature Extraction

Feature extraction plays a crucial role in converting raw EMG signals into meaningful representations by identifying patterns, reducing dimensionality, and enhancing analysis for deep learning models. The Inception Transformer (IT) [19] uses self-attention to model EMG feature interactions with both local (muscle activation) and global (muscle group coordination) dependencies to improve gesture classification accuracy. EMG data are unstructured (waveform features) and structured (numerical signal features). Query-Key-Value Attention mechanism of IT derives EMG signal features' dependencies such as frequency components, muscle activation levels, and temporal variations as described in equations (4):

$$atn(G,E,X) = softmx\left(\frac{GE^{I}}{\sqrt{b_j}}\right)X \tag{4}$$

where, b_j is the feature dimension. This step enables the model to highlight significant EMG signal features and ignore irrelevant variations, which improves classification performance. The Mix-Feed Forward Network (Mix-FFN) improves feature representation by using nonlinear transformations, better enabling the model to distinguish between minor variations in EMG patterns. In addition, skip connections combine outputs of several transformer layers, retaining important signal information while avoiding gradient vanishing, as expressed in equation (5):

$$\frac{A}{2} \times \frac{b}{2} \times O \tag{5}$$

Using self-attention and nonlinear feature transforms, the IT architecture learns and represents EMG features accurately to classify hand gestures, enhancing the predictions made based on patterns of muscle activations and movement intention. This permits fast, high-fidelity, hand-gesture classification in real-time, advantageous to prosthetics, human-machine interface, and assistive rehabilitation devices. Downstream classification models accept these derived features as input and provide high resilience and adaptive learning in the task of EMG signal-to-hand-gesture classification.

2.4. Convolutional Neural Network and Progressive Feedback Residual Attention Network (CNN-PFRAN) based Classification

Following feature extraction, classification is performed. It comprises a Convolutional Neural Network and a Progressive Feedback Residual Attention Network. For the hand gesture classification system using EMG signals, we propose the Convolutional Neural Network and Progressive Feedback Residual Attention Network (CNN-PFRAN) architecture. The explanation is given below in detail as follows:

2.4.1. Convolutional Neural Network (CNN)

Convolutional Neural Networks (CNNs) [20] are effective for classifying Electromyography (EMG) signals by extracting spatial and temporal features from EMG data. The main components of a CNN-based classification system for hand gesture recognition using EMG signals include convolution, pooling, fully connected layers, and classification. The convolutional layer extracts important patterns from EMG signals using convolutional kernels (filters). Given an input EMG feature map Z_b a kernel E_a performs convolution to generate output feature maps D_a as equation (6):

$$D_a = l\left(\sum_{b=1}^{m}(E_a * Z_b) + g_b\right) \tag{6}$$

where, l is the activation function, * represents the convolution operation, g_b is the bias term. Next block pooling reduces the dimensionality of feature maps while retaining essential information. It enhances computational efficiency and robustness. The most common pooling techniques are max pooling and average pooling. After extracting features, the CNN flattens the feature maps into a 1D feature vector and passes them through fully connected layers. The fully connected neurons perform weighted summation is given by equation (7):

$$Full = l\left(g + \sum_{m=1}^{q} v_{1,c} . s_c\right) \tag{7}$$

where, $Full$ is the output of the fully connected layer, s_c is the input from the previous layer, $v_{1,c}$ are the weights, g is the bias term. The final output layer consists of softmax activation to classify hand gestures based on the extracted EMG features. To enhance generalization and prevent overfitting in CNN-based hand gesture classification using EMG signals, techniques like data augmentation (synthetic EMG generation), dropout (random neuron deactivation), batch normalization (stabilizing learning), and early stopping (preventing overtraining) are employed. These methods improve model robustness, ensuring high accuracy and reliable real-time gesture recognition.

2.4.2. Progressive Feedback Residual Attention Network (PFRAN)

The Progressive Feedback Residual Attention Network (PFRAN) [21] improves classification features through residual attention mechanisms to classify hand gestures concerning electromyography (EMG) signals. The residual Attention Stack (RA) function adapts the weight values of significant EMG signal features to reduce unimportant information when processing. Global Average Pooling to Capture Key EMG Features is represented as equation (8):

$$o_p = U_{ca}(w_p) = \frac{1}{U \times X}\sum_{i=1}^{U}\sum_{j=1}^{X} w_p(i,j) \tag{8}$$

Feature Weighting via Attention Mechanism is given by equation (9):

$$c = \beta(Q_X(\gamma(Q_R(o)))) \tag{9}$$

where, Q_X and Q_R are two convolutional layers that compress and reconstruct feature dimensions, β and γ are ReLU and Sigmoid activation functions for non-linearity. The model provides probabilities for different hand gestures, allowing for precise and automatic muscle movement recognition. The PFRAN model continuously improves EMG signal features with attention mechanisms and optimizes classification with structure-aware loss functions. This offers an accurate, strong, and interpretable hand gesture classification of EMG signal patterns. CNN-PFRAN is designed to improve the classification accuracy of EMG-based hand gesture recognition. To enhance the performance of classification with lower error rates, time, complexity, and cost, the CNN-PFRAN model is optimized using the SGA algorithm for hand gesture classification from EMG signals. The hyperparameters optimization procedure for CNN-PFRAN is done by Snow Geese Algorithm (SGA). The detailed architecture of CNN-PFRAN is illustrated in Figure 3.

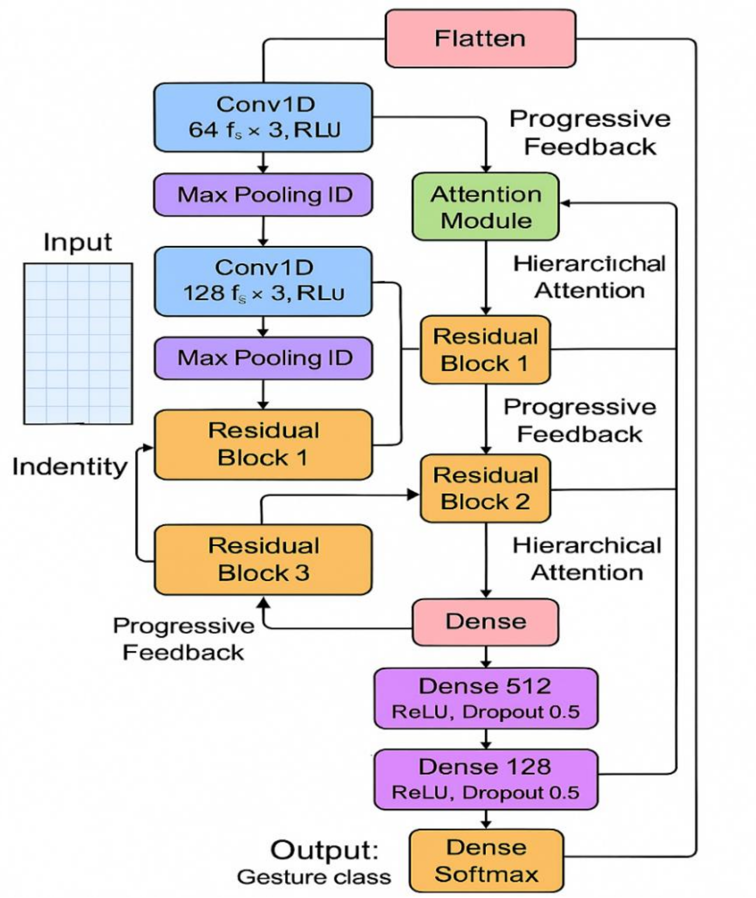

Figure 3: **A detailed architecture of CNN-PFRAN deep learning model.**

2.5 Snow Geese Algorithm (SGA) based Optimization

The Snow Geese Algorithm (SGA) [22], a metaheuristic optimization method inspired by the cooperative migratory behavior of snow geese, is employed to fine-tune the hyperparameters of the CNN-PFRAN model for optimal performance. This nature-inspired algorithm simulates the dynamic formation and directional leadership of geese in flight to explore and exploit the solution space efficiently. Through iterative steps involving population initialization, fitness evaluation, herringbone exploration, and drag-force exploitation, SGA systematically adjusts parameters such as learning rate, weight decay, and dropout rate, enhancing the model's classification accuracy and generalization ability. A step-by-step description of each step of the SGA process to optimize the CNN-PFRAN model's hyperparameters is given as follows:

Step1: Initialization: A starting population is generated for the SGA, and within this population, every individual can be considered as a potential hyperparameters set of the CNN-PFRAN model.

Step 2: Generation of Random Variables: Randomly initialize the optimization variables of the SGA for *searching the search space to obtain an optimal solution.*

Step 3: Evaluation of Fitness Function: The position of each search agent is examined by the fitness function, based on which objective is to find the best minimization of the loss or maximum accuracy with optimal hyperparameters. The fitness function is defined by equation (10):

$$fitnessfuntion = \min_{mise}\left(G_j\right)\max_{mise}\left(G_q\right) \tag{10}$$

where, G_j represents the error rate, processing time, and computational cost. G_q denotes the model's accuracy. $\min_{mise}$ and $\max_{mise}$ are the minimize and maximize coefficients that balance these factors.

Step 4: Exploration for improving accuracy: An optimal solution is obtained by iteratively adjusting the positions of all search agents within the search space. The herringbone pattern facilitates extensive exploration, allowing the algorithm to search for the best solution. A sequence of improvements guides the search agent positions toward the optimal answer, as expressed in equation (11):

$$R_c^{j+1} = R_c^j + b.(R_b^j - R_c^j) + Z_c^{j+1} \tag{11}$$

where, R_b^j is the position of each search agent, and R_c^j represents the current position.

Step 5: Exploitation for reducing the error rate, processing time, computational complexity, and cost: Search agents adjust their positions to optimize hyperparameters, reducing the error rate and processing time while minimizing computational complexity and total cost. This transition is guided by the hyperparameters, with their values revised according to the formula expressed in equation (12):

$$R_c^{j+1} = \begin{cases} R_c^j + (R_c^j - R_b^j).a, & c \geq 0.5 \\ R_b^j + (R_c^j - R_b^j).a \otimes brownian(g), & c \leq 0.5 \end{cases} \tag{12}$$

where, a incorporates the drag force and energy loss to optimize the agents' positions.

Step 6: Termination: The algorithm stops when a stopping criterion I is reached, e.g., the attainment of a predetermined number of iterations or a satisfactory fitness value. The process of optimization comes to an end when the stopping conditions are satisfied through various iterations.

This section puts forth the suggested Convolutional Neural Network and Progressive Feedback Residual Attention Network with Snow Geese Algorithm (CNN-PFRAN+SGA) framework for the EMG Signals-Based Hand Gesture Classification System. The proposed framework uses various state-of-the-art techniques, thereby achieving better accuracy and reliability in classification. The framework uses an APMF for preprocessing to eliminate noise and enhance signal quality; this is followed by IT-based feature extraction to grab relevant EMG signal features. Due to its capability to perform deep learning and thus efficiently recognize a plethora of complex hand gestures, the CNN-PFRAN model comes next in line for classification. To do even better, the SGA is further integrated to optimally adjust system and network performance parameters. Working towards enhancing system classification precision minimizing computational complexity and maximizing adaptability, hybrid approaches are implemented. The next section will discuss in detail the experimental results obtained using the given method.

3. Results and Discussions

This section presents the experimental outcomes and evaluates the performance of the proposed CNN-PFRAN model optimized using SGA for EMG-based gesture recognition. The results are analyzed in terms of classification accuracy, latency, and robustness across multiple gesture classes. Comparative evaluations with existing baseline models are also included to highlight the effectiveness of the proposed architecture. Furthermore, visual and statistical interpretations are provided to support the findings and demonstrate the model's practical applicability in real-time gesture recognition systems. Details on the study of the proposed method are in the well-thought comparisons section as it has been presented through MATLAB experiments.

3.1. Performance Analysis of Proposed Methods

This section evaluates the effectiveness of the proposed method by analyzing various performance metrics [23], [24]. Table 1 provides a detailed comparison of the model's performance against existing methods, highlighting its strengths and capabilities. This performance comparison table highlights the superiority of the proposed CNN-PFRAN model optimized with SGA over existing methods. Achieving an outstanding accuracy of 99.9%, specificity of 99.5%, and precision of 99.7%, the proposed model significantly outperforms traditional architectures such as VMD-CNN LSTM, CNN, CNN-LSTM, and LSTM-MSA. Notably, it also achieves the lowest error rate of just 0.2% and the fastest computational time of 0.20 seconds, indicating its suitability for real-time applications. Furthermore, the CNN-PFRAN+SGA model delivers an exceptional F1-score of 99.8%, reflecting its robust and balanced classification performance. Overall, the proposed method demonstrates marked improvements in both accuracy and efficiency, validating its effectiveness for EMG-based gesture recognition tasks. The comparison of performance metrics of various considered DL models is illustrated through Figure 4.

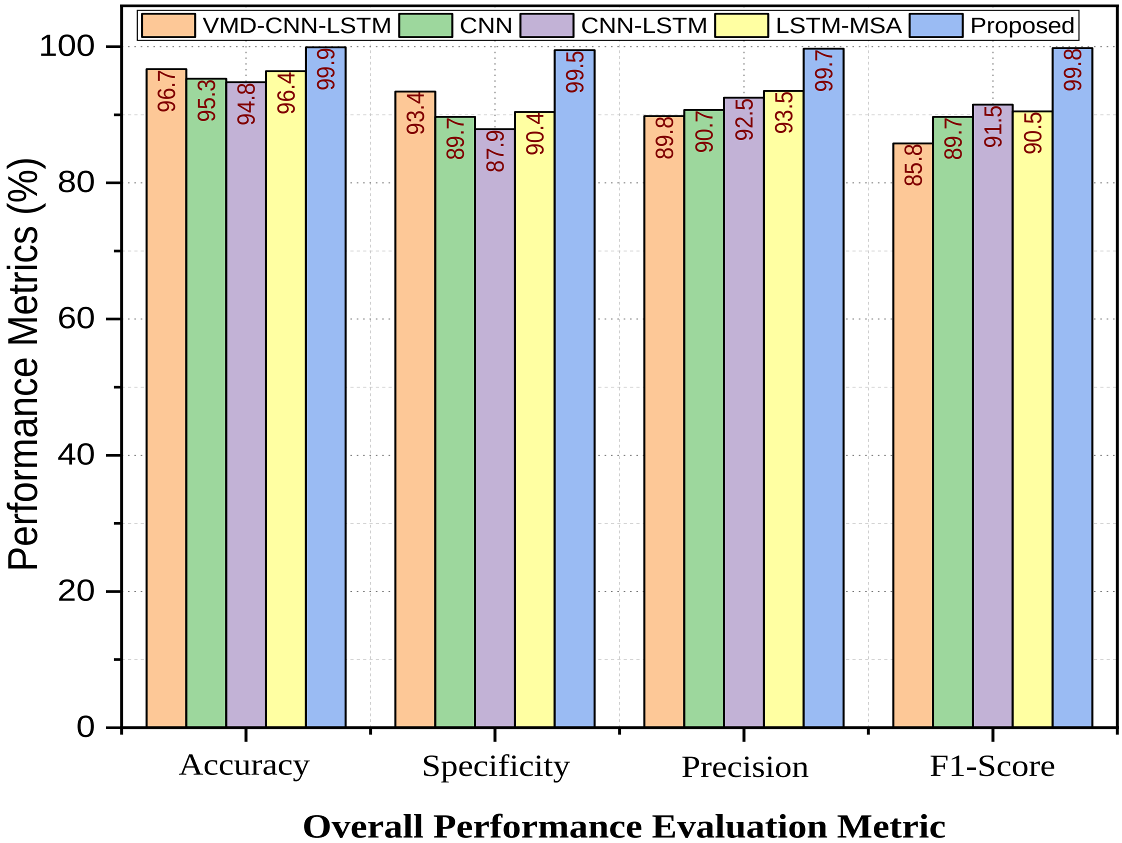

Figure 4: Comparison of performance of various considered DL models with proposed model.

Table 1: Comparison of the Model's Performance with the Proposed Method

Methods Performance	Accuracy (%)	Specificity (%)	Precision (%)	Computational time (sec)	Error rates (%)	F1-score (%)
VMD-CNN LSTM [11]	96.7	93.4	89.8	0.58	3.5	85.8
CNN [12]	95.3	89.7	90.7	0.66	7.5	89.7
CNN-LSTM [13]	94.8	87.9	92.5	0.50	5.6	91.5
LSTM-MSA [14]	96.4	90.4	93.5	0.65	6.3	90.5
CNN+PFRAN+SGA (Proposed)	**99.9**	**99.5**	**99.7**	**0.20**	**0.2**	**99.8**

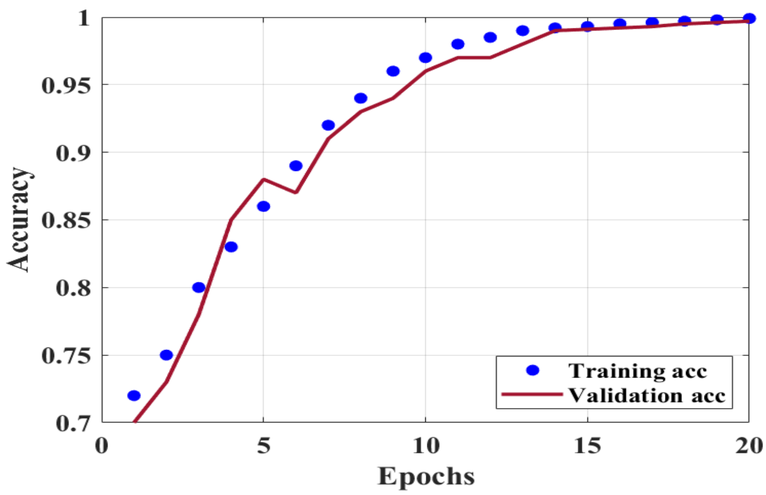

Figure 5: Training vs. validation accuracy over epochs

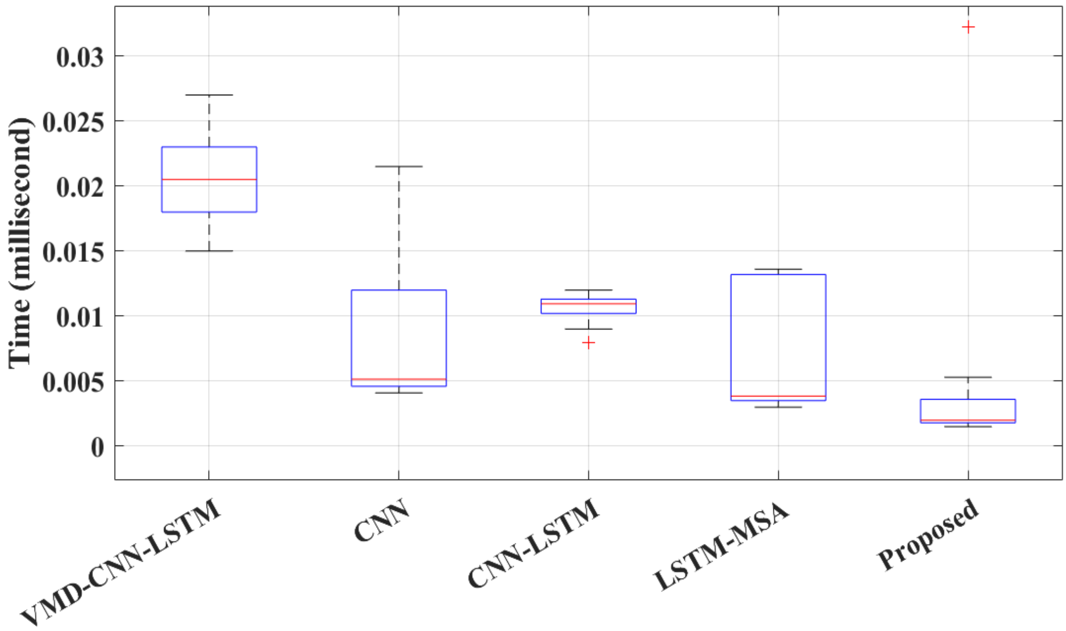

Figure 6: The comparison of computation time of the proposed method

The effectiveness and efficiency of the proposed model are further demonstrated through training dynamics and computational performance, as depicted in Figures 5 and 6. Figure 5 illustrates training and validation accuracy over 20 iterations. Blue dots indicate training accuracy, and the red line indicates validation accuracy. The curves rise and meet close to 1, which is indicative of good model performance. There is a little gap, so there is hardly any overfitting, with training accuracy marginally greater than validation accuracy through training. Figure 6 shows the computation time comparison of the proposed method.

4. Conclusion

The study presents a comprehensive end-to-end framework for EMG-based gesture recognition using a deep learning approach optimized with metaheuristic techniques. In this manuscript, a novel CNN-PFRAN model optimized using SGA has been successfully implemented for robust EMG-based gesture recognition. The system successfully integrates APMF, advanced feature extractor (Inception Transformer), and optimized hybrid classification model (CNN-PFRAN with SGA) to address critical challenges in noise robustness, computational efficiency, and generalization. Experimental results on the UC2018 DualMyo dataset demonstrate breakthrough performance, achieving 99.9% accuracy with 0.20ms latency which surpasses existing methods by 3.2 to 5.1% while meeting clinical real-time requirements. These advancements position the framework as a transformative tool for prosthetic control, rehabilitation robotics, and immersive human-computer interaction. Future work can explore hybrid optimization strategies, extend the system for multi-user adaptability, and develop real-time applications in assistive robotics, prosthetics, and virtual reality.

Declarations

Ethical Approval

There were no human subjects or animals used in this investigation. The study is based only on the examination of publically accessible data; no new data were gathered from people or animals for this work.

Declaration of Competing Interest

The authors declare no competing financial or personal interests influencing this work.

Disclosure of Potential Conflicts of Interest

The authors declare that they have no conflicts of interest.

Availability of data and materials

The research is based solely on the analysis of publicly available UC2018 DualMyo Hand Gesture Dataset (Simão et al., 2018, Zenodo, v1.0-alpha). https://doi.org/10.5281/zenodo.1320922

Informed consent

Not applicable.

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