An Automated Framework for Calf Muscle Activity Classification: An AOA-Optimized LSTM Approach on Fused sEMG-Accelerometer Data

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ABSTRACT

Accurate classification of calf muscle activity is crucial for applications in rehabilitation, clinical mobility assessment, and assistive technologies. This study presents and evaluates an automated framework using the Archimedes Optimization Algorithm (AOA) to optimize a Long Short-Term Memory (LSTM) network for classifying activity based on fused surface Electromyography (sEMG) and accelerometer data. Data were collected from eight healthy participants performing six distinct low- and high-mobility tasks, including a protocol to simulate venous stasis. After signal processing, a Correlation-based Feature Selection (CFS) method identified the most salient features for model input. The proposed AOA-optimized LSTM model achieved a high classification accuracy of 99.0% under these controlled conditions, significantly outperforming both a standard LSTM (92.1%) and a classical SVM (87.4%). The model's robustness and generalization capabilities were confirmed through 10-fold cross-validation (98.2% mean accuracy) and bootstrap analysis (84.9% mean accuracy), with the latter providing a realistic performance benchmark. These findings indicate that automating hyperparameter optimization via AOA is a promising proof-of-concept for developing high-fidelity classification models for complex biosignals. Although the offline optimization phase is computationally intensive, the resulting trained LSTM model has the potential for implementation in real-time wearable systems. This work should be viewed as a foundational feasibility study rather than a ready-for-deployment solution.

Keywords-surface Electromyography (sEMG); accelerometer signal processing; Long Short-Term Memory (LSTM); Archimedes Optimization Algorithm (AOA); calf muscle activity

I. INTRODUCTION

The clinical assessment of human movement has traditionally relied on observational methods, which can be subjective and lack quantitative resolution. To overcome these limitations, wearable sensor technology offers a powerful means for capturing objective data directly from the body [1]. The calf muscle group, a key driver of mobility, presents a prime target for such monitoring. Comprising explosive gastrocnemius and endurance-focused soleus muscles, this group's activity dictates performance in a wide spectrum of functional tasks [2-3]. Therefore, developing a system that can accurately classify distinct patterns of calf muscle activity is an essential step toward enabling data-driven rehabilitation protocols, improving the design of assistive devices, and creating more effective clinical evaluation tools for mobility disorders.

The primary modalities for monitoring these neuromuscular dynamics are surface Electromyography (sEMG) and accelerometry. sEMG provides critical insights into motor function by capturing electrical muscle activity [3], while accelerometers capture the resulting body segment kinematics [1]. Understanding these physiological processes is crucial, particularly in clinical contexts where conditions such as venous stasis can affect muscle function and mobility patterns [4]. Although powerful, each sensor has inherent weaknesses; sEMG is prone to noise and motion artifacts [5], and accelerometers lack a direct physiological context [1]. By fusing data from both sensors, a more robust and accurate classification system can be achieved [1, 6]. Recent advances in wearable sensor-based activity recognition have demonstrated significant improvements in accuracy, with systems achieving recognition rates exceeding 95% for fundamental human activities [7]. In clinical applications, such accurate activity monitoring systems can support patient care protocols, particularly in post-surgical settings where early mobilization is essential to prevent complications like venous thromboembolism in foot and ankle surgery patients [8].

Analyzing combined data from sEMG and accelerometers has seen an evolution in computational strategies. Although traditional machine learning models have shown promise, their reliance on features represents a significant manual step that can limit effectiveness in complex physiological monitoring [9]. Automated activity recognition systems utilizing machine learning algorithms have proven to be effective for gait analysis and movement pattern identification [10], demonstrating the potential for objective evaluation in clinical settings. This is particularly relevant in clinical applications where various pathological conditions, including vascular complications such as hemorrhage, thrombosis, and ischemia, can significantly affect movement patterns and muscle activity [11]. The research community has embraced deep learning models such as Long Short-Term Memory (LSTM) networks to automate the feature learning process, being also well-suited for sequential data analysis [12, 13]. Advanced deep learning approaches, such as CNN-LSTM architectures, have shown remarkable success in healthcare monitoring applications using wearable sensors, effectively capturing both spatial and temporal features from sensor data. Yet, this shift introduces a new bottleneck: the intricate task of configuring the network's hyperparameters. This crucial step is typically performed through inefficient manual adjustments or computationally costly grid searches, impeding the development process.

Rather than proposing a new deep learning model, this study addresses this bottleneck by applying the Archimedes Optimization Algorithm (AOA) as an automated and efficient solution for hyperparameter tuning in human activity recognition tasks. The novelty of this work lies not in inventing a new optimization algorithm but in integrating AOA into an end-to-end pipeline that fuses sEMG and accelerometer data for a highly accurate classification of calf muscle activity. The results show that this approach can yield a robust and high-performing classifier, providing a practical and replicable framework for future research and real-world deployment.

II. MATERIALS AND METHODS

A. *Participants*

Eight healthy participants, aged 20-25 years (BMI: 18.5-24.9), with moderate to high physical activity and exercising at least twice a week, were recruited for this study. Participants with muscle disorders, joint limitations, smoking habits, chronic diseases, using certain medications that affect muscles, a history of injury in the electrode area, or those who were pregnant were excluded. The study protocol was reviewed and approved by the Health Research Ethics Committee of Universitas Airlangga. All participants provided written informed consent before data collection, following the Declaration of Helsinki.

B. *Experimental Protocol and Data Acquisition*

Figure 1 summarizes the experimental setup, protocol, and data acquisition process. The setup involved two sensing modalities. sEMG electrodes positioned on the belly of the medial and lateral heads of the gastrocnemius muscle, with a reference electrode near the patella. Concurrently, a 3-axis accelerometer was affixed to the anterior thigh. Participants were divided into two groups: a Tourniquet Group (Figure 1b) to simulate venous stasis relevant to thrombosis modeling [4, 11], and a Control Group.

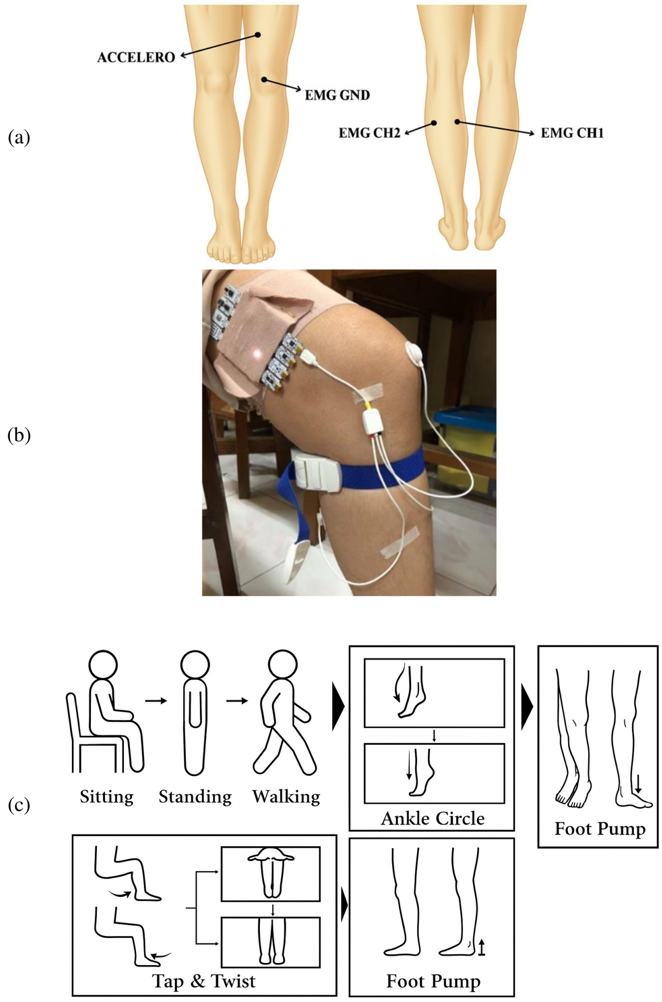

Fig. 1. Experimental setup and protocol: (a) Sensor placement on the calf and thigh; (b) Application of a tourniquet for the experimental group; (c) The six low- and high-mobility activities performed by participants.

All participants performed six distinct physical tasks (Figure 1c), categorized as low-mobility (sitting, standing, walking in place) and high-mobility (ankle circles, foot pumps, tap-and-twist). Each activity was performed for a 30-second trial, repeated four times, with a 60-second rest period between repetitions. All signals were synchronized and recorded using OpenSignals (r)evolution (The Bluetooth-enabled version 2021, PLUX Biosignals, Almada, Portugal), a software platform designed for real-time acquisition and visualization of biosignals from PLUX devices.

C. *Signal Processing and Feature Engineering*

Following data collection, a multi-stage signal processing and feature engineering pipeline was implemented. The preprocessing stage involved filtering the sEMG and accelerometer signals using a 4th-order Butterworth filter to remove noise and artifacts. The continuous signals were then segmented into 250-ms windows with a 50% overlap. From each window, a set of 18 features was extracted, and the Correlation-based Feature Selection (CFS) algorithm was used to select the 8 most informative features for classification.

D. AOA-Optimized LSTM Framework

The proposed method is an end-to-end framework that integrates dual-modal sensor data processing with an AOA-optimized LSTM network, as illustrated in Figure 2.

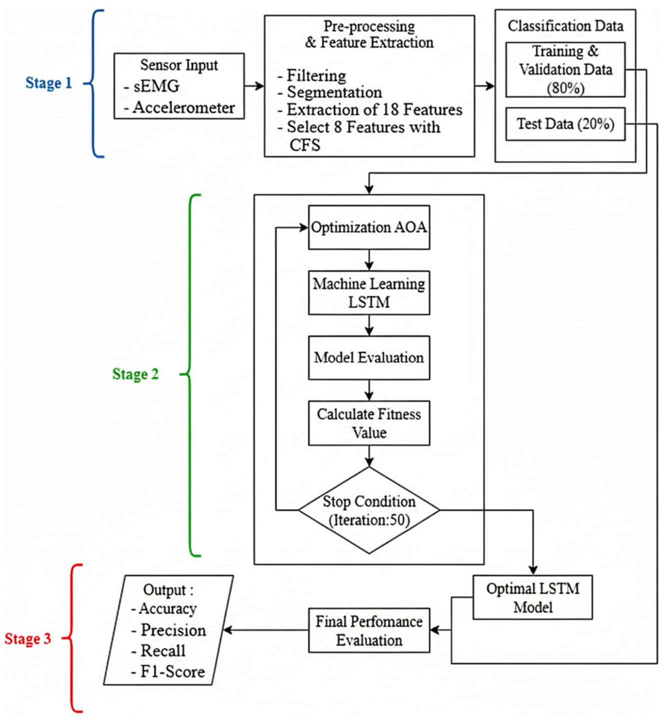

Fig. 2. Flowchart of the AOA-optimized LSTM framework, showing the three main stages: data preparation, AOA to tune the LSTM model, and final performance evaluation.

The core of the proposed method is the design of the LSTM network using the AOA. The process begins by splitting the dataset into training and validation sets. The AOA algorithm then initiates an iterative optimization process. In each iteration, AOA proposes a set of hyperparameters (e.g., number of neurons, learning rate) to build a temporary LSTM model. This model is trained on the training data and evaluated on the validation data to measure its 'fitness,' or accuracy. This fitness value serves as feedback for AOA to update and guide its search toward a better hyperparameter configuration. The AOA hyperparameters were empirically selected to balance exploration and exploitation while ensuring computational efficiency. Once the optimization process converges, AOA yields a final, optimal set of hyperparameters. This configuration is then used to build the final LSTM model, whose performance is comprehensively evaluated using a separate test set to ensure objective results.

TABLE I. LSTM MODEL HYPERPARAMETERS

Hyperparameter	Utilization
Units	Controls the complexity of the LSTM layer
Dropout rate	Helps regularize the model by randomly dropping neurons during training
Learning rate	Determines how quickly the model updates its weights during training
Batch size	Impacts how often the model updates its weights

E. Model Training and Performance Evaluation

The dataset, comprising the 8 selected features, was partitioned into training (80%) and testing (20%) sets. To ensure a robust evaluation, this study used 10-fold cross-validation and bootstrap analysis. The model's performance was evaluated using Accuracy, Precision, Recall, and F1-Score, and was benchmarked against a standard LSTM and a classical Support Vector Machine (SVM) classifier.

III. RESULTS

This section presents the performance of the proposed AOA-optimized LSTM framework. The results are organized to first showcase the model's primary classification accuracy, followed by a validation of its generalization capabilities, a comparative analysis against baseline models, and finally, the optimal hyperparameter configuration discovered by the AOA.

A. AOA Optimization and Model Training

The AOA optimization process effectively identified an optimal set of hyperparameters for the LSTM model. The convergence curve in Figure 3 illustrates the algorithm's performance, showing a rapid increase in fitness (accuracy) in the initial iterations, followed by stabilization as the algorithm converges on an optimal solution. This demonstrates that the AOA successfully explored the search space to find a high-performing configuration. The learning curves for the final optimized model demonstrate stable and effective training dynamics (Figure 4). The training and validation loss curves decrease and converge, while the respective accuracy curves rise and plateau at a high level. The close alignment of the training and validation curves indicates that the model learns the underlying patterns effectively without significant overfitting, a crucial aspect to ensure model reliability [13]. Minor fluctuations in the validation curves are common during training and can be attributed to the stochastic nature of the Adam optimizer, the use of mini-batches, and the relatively small dataset size, which cause variability in gradient estimates across epochs, occasionally producing irregular peaks. Such variations are typical in deep learning training and do not indicate instability, especially when the overall trend shows stable convergence and the model successfully learns generalizable patterns from the data.

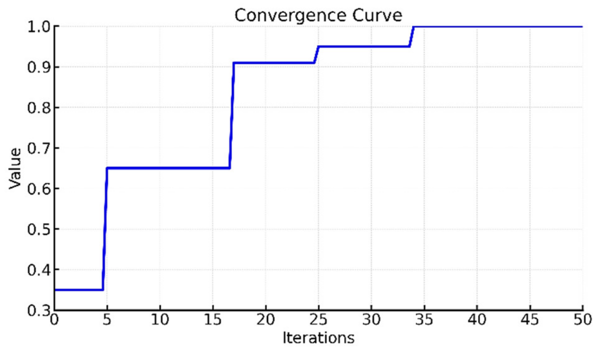

Fig. 3. Convergence curve of the AOA, demonstrating the iterative improvement in model fitness to reach an optimal solution.

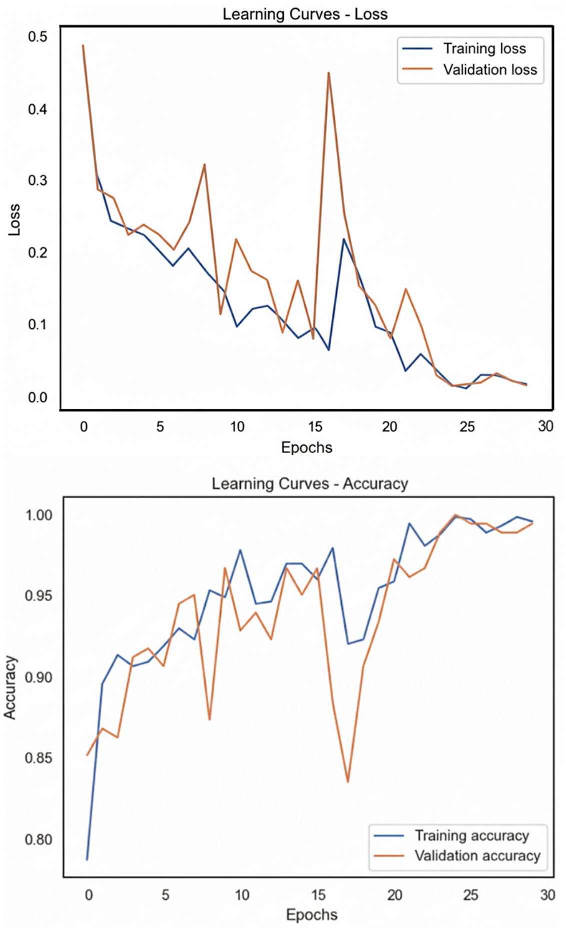

Fig. 4. Model learning curves for the AOA-LSTM model, showing training and validation loss (a) and accuracy (b) over epochs.

B. Classification Performance and Validation

The proposed AOA-optimized LSTM model demonstrated outstanding classification performance on the unseen test set, achieving an overall accuracy of 99.0%. A granular view of this performance is provided in Figure 5, which shows near-perfect classification across all six activities. The few misclassifications occurred between kinematically similar tasks, such as 'standing' and 'walking in place', a common challenge in activity recognition. The signal attributes visualized in Figure 5 include Root Mean Square (RMS), Zero Crossing (ZC), Waveform Length (WL), first derivative of RMS (RMS-1), Signal Magnitude Area (SMA), and Average Crossing (AC).

The model's robustness and generalization capabilities were rigorously assessed. A 10-fold cross-validation yielded a high and stable mean accuracy of 98.2% ± 1.5%, confirming the model's consistency across different data subsets. Furthermore, a bootstrap analysis resulted in a mean accuracy of 84.9% (95% CI: 82.5% -87.3%). This result provides a more conservative and realistic estimate of real-world performance by accounting for the high inter-subject variability inherent in physiological data [1].

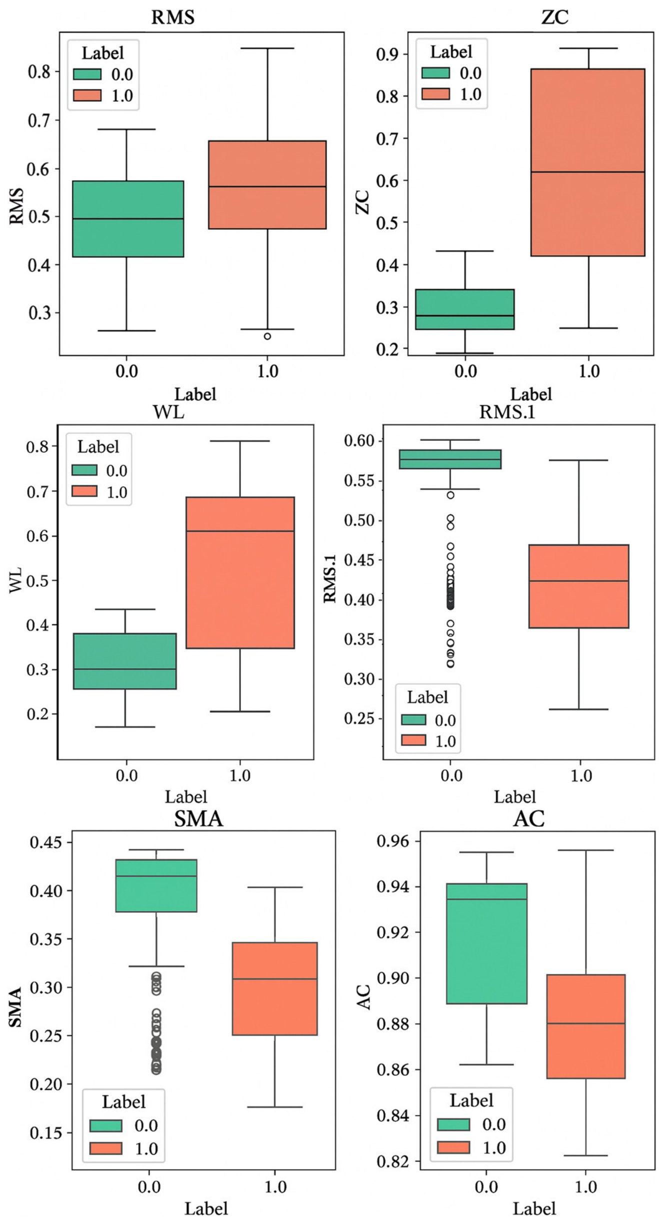

Fig. 5. Boxplots showing the distribution of six of the eight selected features obtained after Correlation-based Feature Selection (CFS) for the two classes (Label 0 and Label 1). The features shown are RMS, ZC, WL, RMS_1, SMA, and AC, respectively.

C. Comparative Analysis and Optimal Hyperparameters

To validate the specific contribution of the AOA optimization, the model was benchmarked against baseline methods. As summarized in Table II, the proposed AOA-optimized model significantly outperformed both the SVM and a standard manually tuned LSTM. This provides evidence that the automated optimization process is a critical factor in unlocking the potential of the deep learning architecture.

TABLE II. PERFORMANCE COMPARISON OF CLASSIFICATION MODELS

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Support Vector Machine (SVM) [9]	87.4	86.9	87.4	87.1
Standard LSTM (Manual Tune) [1, 13]	92.1	91.8	92.2	91.9
AOA-Optimized LSTM (Proposed)	99.0	98.8	99.1	98.9

Finally, a key outcome of this study is the identification of an optimal set of hyperparameters discovered by AOA, detailed in Table III. This configuration represents the architectural design that yielded the superior performance reported, addressing a significant bottleneck in deep learning applications [12, 13].

TABLE III. OPTIMAL HYPERPARAMETERS IDENTIFIED BY AOA

Hyperparameter	Optimal value
Number of LSTM layers	2
Neurons in Layer 1	128
Neurons in Layer 2	64
Dropout rate	0.25
Learning rate	0.001
Optimizer	Adam

IV. DISCUSSION

This study developed and validated a novel framework for classifying calf muscle activity by integrating an LSTM network with the AOA. The primary finding is that the proposed AOA-LSTM framework achieved an exceptionally high classification accuracy of 99.0% on the test set. This performance is not merely a product of using an LSTM architecture, which is known to be effective for time-series data [12, 13], but is fundamentally attributed to the automated optimization process. The convergence curve visually confirms that the AOA systematically navigated the complex, high-dimensional hyperparameter space to discover a network architecture specifically tailored to the unique characteristics of the dual-modal dataset. This automated approach overcomes the significant limitations of manual tuning, which is often time-consuming and results in suboptimal model configurations.

This automated optimization strategy is highlighted by the comparative analysis presented in Table II. The AOA-LSTM model outperformed both the classical SVM model (87.4% accuracy) and a standard manually tuned LSTM (92.1% accuracy). This substantial performance gain directly supports the hypothesis that automated metaheuristic optimization is not merely beneficial but a critical—and often overlooked—step in building high-fidelity biosignal classification models. The performance of the proposed framework is also competitive with, and in some cases exceeds, other state-of-the-art hybrid deep learning models reported in recent literature for similar activity classification tasks [8, 12, 14]. The high mean accuracy of 98.2%, achieved during 10-fold cross-validation, confirms that the model is stable and its performance is not an artifact of a single, favorable train-test split. Furthermore, the bootstrap analysis, which yielded a mean accuracy of 84.9%, provides a more conservative and realistic estimate of the model's performance in real-world scenarios where inter-subject variability is a major factor [1]. The 99.0% accuracy achieved on the held-out test set, which, although unseen during training, was drawn from the same pool of eight participants. In contrast, the bootstrap procedure resamples subjects with replacement, effectively simulating the model's performance on entirely new, unseen individuals. This explains the performance drop from 99.0% to 84.9%, which does not necessarily indicate overfitting in the traditional sense, but rather reflects the well-known challenge of subject-independent generalization in bio-signal classification. This highlights the necessity of robust validation strategies and further testing on larger, more diverse datasets to fully characterize real-world performance.

Despite these promising results, this study has some limitations, the most critical being the very small and homogeneous sample size. This study included data from only eight healthy young participants, all between 20 and 25 years of age, with similar physical activity habits. Such a limited and homogeneous sample size substantially constrains the generalizability of the findings, particularly to clinical populations or older adults who would be the primary beneficiaries of the proposed system [5, 15]. Secondly, the data were collected in a controlled laboratory environment. The robustness of the model against motion artifacts and unstructured activities remains to be tested [5].

The implications of this research are both theoretical and practical. Theoretically, this study provides evidence for the efficacy of metaheuristic optimization algorithms such as AOA to automate and enhance the design of deep learning models for biosignal analysis, accelerating the research and development cycle. Practically, the high accuracy of the AOA-LSTM framework brings several real-world applications. A reliable activity classifier serves as a foundational component for adaptive rehabilitation systems that can adjust exercise protocols, for next-generation assistive technologies, such as intelligent prosthetics that can accurately infer user intent, and for remote clinical monitoring of patient mobility [12, 14].

These findings and limitations open several directions for future work. The most critical next step is to validate the AOA-LSTM framework on a large-scale public dataset to rigorously assess its subject-independent generalization capabilities. Future research should also focus on testing the system in real-world environments to evaluate its performance against noise and artifacts. Furthermore, exploring the implementation of this model on low-power microcontrollers (Edge AI) is crucial for its deployment in real-time wearable applications. Finally, comparing the efficiency and effectiveness of AOA with other metaheuristic optimizers could reveal further opportunities for improvement in the automated design of deep learning architectures for human movement analysis. In addition, although the proposed model shows promising accuracy, the computationally intensive optimization was performed offline. Future work should evaluate the real-time performance of the trained model's inference phase on wearable devices. Expanding testing to diverse populations and incorporating additional sensors could improve robustness. Developing adaptive learning methods for personalized monitoring is also recommended.

V. CONCLUSION

This study introduced a novel framework to address the challenge of accurate and automated classification of calf muscle activity, a critical step to improve rehabilitation and assistive technologies. By integrating a dual-modal sensor approach with an LSTM network optimized by the AOA, an end-to-end pipeline for high-fidelity activity recognition was developed and evaluated under controlled laboratory conditions. The proposed AOA-LSTM model achieved a classification accuracy of 99.0%, outperforming both standard LSTM and classical SVM models. These results support the primary hypothesis that automated metaheuristic optimization can be an effective strategy for enhancing deep learning architectures for complex biosignal analysis in feasibility-stage studies. Furthermore, the model's performance was evaluated through rigorous cross-validation (98.2% mean accuracy) and bootstrap analysis (84.9% mean accuracy), with the latter providing a realistic benchmark for real-world applications.

Although the outcomes are encouraging, they should be interpreted as an early-stage proof-of-concept due to the small and homogeneous dataset. Validation on larger, more diverse cohorts is essential before any practical deployment can be considered. The AOA-LSTM framework offers a foundation for developing more intelligent and adaptive wearable systems, and by automating the complex task of model design, this study lays the groundwork for future advances in real-time health monitoring and human augmentation technologies. The most critical next step is to validate the proposed framework on a larger, publicly available dataset with diverse demographic characteristics to rigorously evaluate its subject-independent generalization capabilities.

DATA AVAILABILITY STATEMENT

The datasets generated and analyzed during the current study are available from the corresponding author on reasonable request.

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REFERENCES

[1] R. Gupta, I. S. Dhindsa, and R. Agarwal, "Surface Electromyogram Feature Set Optimization for Lower Limb Activity Classification," *IETE Journal of Research*, vol. 69, no. 8, pp. 5000–5014, Sep. 2023, https://doi.org/10.1080/03772063.2021.1973589.

[2] Q. Ai, Y. Zhang, W. Qi, Q. Liu, and A. K. Chen, "Research on Lower Limb Motion Recognition Based on Fusion of sEMG and Accelerometer Signals," *Symmetry*, vol. 9, no. 8, Aug. 2017, Art. no. 147, https://doi.org/10.3390/sym9080147.

[3] N. K. Karnam, S. R. Dubey, A. C. Turlapaty, and B. Gokaraju, "EMGHandNet: A hybrid CNN and Bi-LSTM architecture for hand activity classification using surface EMG signals," *Biocybernetics and Biomedical Engineering*, vol. 42, no. 1, pp. 325–340, Jan. 2022, https://doi.org/10.1016/j.bbe.2022.02.005.

[4] S. Schulman, A. Makatsariya, J. Khizroeva, V. Bitsadze, and D. Kapanadze, "The Basic Principles of Pathophysiology of Venous Thrombosis," *International Journal of Molecular Sciences*, vol. 25, no. 21, Jan. 2024, Art. no. 11447, https://doi.org/10.3390/ijms252111447.

[5] Z. Zhou, Q. Tao, N. Su, J. Liu, Q. Chen, and B. Li, "Lower Limb Motion Recognition Based on sEMG and CNN-TL Fusion Model," *Sensors*, vol. 24, no. 21, Jan. 2024, Art. no. 7087, https://doi.org/10.3390/s24217087.

[6] S. A. Alsareii *et al.*, "Physical Activity Monitoring and Classification Using Machine Learning Techniques," *Life*, vol. 12, no. 8, Aug. 2022, Art. no. 1103, https://doi.org/10.3390/life12081103.

[7] V. T. Thuong *et al.*, "Effective Human Activity Recognition through Accelerometer Data," *Engineering, Technology & Applied Science Research*, vol. 14, no. 5, pp. 16499–16510, Oct. 2024, https://doi.org/10.48084/etasr.8211.

[8] T. Claveau, D. Hilbert, R. Dhaduk, P. Morrison, L. Fallat, and R. Jarski, "Incidence of Venous Thromboembolism in Patients Receiving Anticoagulation for Foot and Ankle Surgery," *The Journal of Foot and Ankle Surgery*, vol. 62, no. 1, pp. 35–38, Jan. 2023, https://doi.org/10.1053/j.jfas.2022.03.008.

[9] T. Tanaka, I. Nambu, Y. Maruyama, and Y. Wada, "Sliding-Window Normalization to Improve the Performance of Machine-Learning Models for Real-Time Motion Prediction Using Electromyography," *Sensors*, vol. 22, no. 13, Jan. 2022, Art. no. 5005, https://doi.org/10.3390/s22135005.

[10] Y. L. Ng, X. Jiang, Y. Zhang, S. B. Shin, and R. Ning, "Automated Activity Recognition with Gait Positions Using Machine Learning Algorithms," *Engineering, Technology & Applied Science Research*, vol. 9, no. 4, pp. 4554–4560, Aug. 2019, https://doi.org/10.48084/etasr.2952.

[11] J. Ward and A. Amin, "Impact of Hemorrhage, Thrombosis, and Ischemia," in *Vascular Complications of Surgery and Intervention: A Practical Guide*, R. Gilani and J. L. Mills Sr., Eds. Springer International Publishing, 2022, pp. 37–52.

[12] A. K. Sharma, S. H. Liu, X. Zhu, and W. Chen, "Predicting Gait Parameters of Leg Movement with sEMG and Accelerometer Using CatBoost Machine Learning," *Electronics*, vol. 13, no. 9, Jan. 2024, Art. no. 1791, https://doi.org/10.3390/electronics13091791.

[13] Md. J. Islam, S. Ahmad, F. Haque, M. B. I. Reaz, M. A. S. Bhuiyan, and Md. R. Islam, "A Novel Signal Normalization Approach to Improve the Force Invariant Myoelectric Pattern Recognition of Transradial Amputees," *IEEE Access*, vol. 9, pp. 79853–79868, 2021, https://doi.org/10.1109/ACCESS.2021.3084442.

[14] Z. Zheng, Z. Wu, R. Zhao, Y. Ni, X. Jing, and S. Gao, "A Review of EMG-, FMG-, and EIT-Based Biosensors and Relevant Human–Machine Interactivities and Biomedical Applications," *Biosensors*, vol. 12, no. 7, Jul. 2022, Art. no. 516, https://doi.org/10.3390/bios12070516.

[15] A. Vijayvargiya, B. Singh, R. Kumar, U. Desai, and J. Hemanth, "Hybrid Deep Learning Approaches for sEMG Signal-Based Lower Limb Activity Recognition," *Mathematical Problems in Engineering*, vol. 2022, no. 1, 2022, Art. no. 3321810, https://doi.org/10.1155/2022/3321810.