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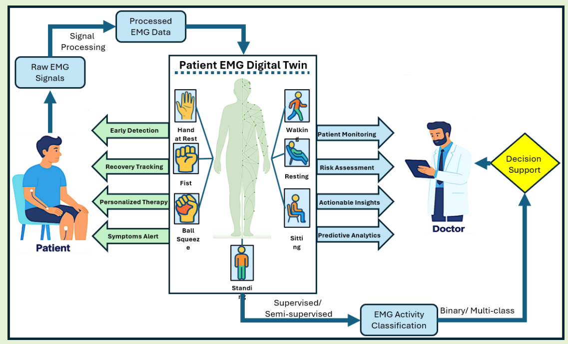
AI-Driven EMG Monitoring and Decision Support Framework

Sagheer Khan, Usman Anwar, Kiran Khurshid, Rahmat Ullah, Tughrul Arslan, *Senior Member, IEEE*, Moataz Ahmed

***Abstract*—Digital Twin (DT) technology, a core pillar of Healthcare 4.0 (H4.0), enables intelligent, non-invasive, and personalized patient monitoring. This research presents a pilot AI-enabled Electromyography (EMG)-driven DT framework for muscular activity assessments. The EMG data enables monitoring of muscle engagements and provides a comprehensive representation of physiological states. The raw EMG data, consisting of 7 activities, i.e., Sitting, Standing, Walking, Relax, Stress Ball, Hand at Rest, and Fist, is subjected to denoising techniques of mean removal, smoothing, and digital filtering. Within the DT model, AI serves as the intelligence core that transforms these denoised signals into relevant digital states. Supervised and semi-supervised classifiers act as inference engines, continuously refining the DT as new data is incorporated, allowing it to evolve in synchrony with the patient's condition. The decision support using ML and DL is employed for EMG classification, utilizing statistical features and autonomous feature extraction methodologies of AutoEncoder (AE) and Stacked AutoEncoder (SAE). The feature data is enriched and enlarged through Gaussian noise feature data augmentation for both feature extraction approaches. The Fine KNN algorithm provides classification accuracy of 94.6% and 91.6%. However, the autonomous feature extraction through the SAE (32-16-32) with Medium KNN provides an overall accuracy of 96.4% and 93.3%. The promising results validate the effectiveness of the proposed framework as a dynamic, AI-driven DT system for prospective holistic patient multi-physiological monitoring and decision support.**



***Index Terms*—Digital Twin, Electromyography, Classification, Multi-Physiological, Signal Processing, Machine Learning, Deep Learning**

I. Introduction

SKELETAL muscle, the largest organ in the human body, facilitates movement through coordinated muscle fiber contractions. However, repetitive motion, poor posture, and excessive muscular exertion can lead to fatigue and degenerative changes, resulting in Musculoskeletal Disorders (MSDs) [1] such as myopathy, neuropathy, tendonitis, and fibromyalgia. These conditions are often painful, debilitating, and a major cause of long-term disability [2]. MSDs account for approximately 2% of the European Union's (EU) gross domestic product (GDP) in annual direct medical expenses [3]. With the global population aging rapidly, the burden of medical expenses is expected to rise substantially. In response, the digital revolution is reshaping healthcare systems worldwide, making services more accessible, cost-effective, and efficient. Advancements in Information and Communication Technology (ICT) play a crucial role in extending healthcare delivery beyond geographical and social limitations.

One such diagnostic and monitoring technology gaining prominence in the context of MSDs and digital healthcare is Electromyography (EMG). EMG signals carry crucial information about muscle activity, originating from electrical impulses generated by the central nervous system. These impulses propagate into neuromuscular junctions and travel along muscle fibers toward the tendons, where they initiate muscle contractions by enabling sarcomere filaments to slide past each other. The central nervous system controls the strength and speed of these contractions by modulating the number of motor units activated and their firing rates. Surface Electromyography (sEMG), recorded from electrodes placed on the skin, captures the combined Motor Unit Action Potentials (MUAPs) within the detection area [4], [5]. EMG can

Sagheer khan is from SDAIA-KFUPM Joint Research Center for Artificial Intelligence (JRCAI), King Fahd University of Petroleum & Minerals (KFUPM), Dhahran, 31261, Saudi Arabia (e-mail: sagheer.khan@kfupm.edu.sa).

Usman Anwar is from School of Engineering, The University of Edinburgh, Edinburgh EH9 3FF, U.K. (e-mail: usman.anwar@ed.ac.uk).

Kiran Khurshid is from National University of Sciences and Technology, Islamabad, 44000, Pakistan (e-mail: kiran.khurshid@ceme.nust.edu.pk).

Rahmat Ullah is from School of Computer Science and Electronic Engineering, University of Essex, Wivenhoe Park, Colchester, CO4 3SQ, Essex, United Kingdom (e-mail:rahmat.ullah@essex.ac.uk).

Tughrul Arslan is with the School of Engineering, The University of Edinburgh, Edinburgh EH9 3FF, U.K and Advanced Care Research Centre (ACRC), The University of Edinburgh, Edinburgh, EH16 4UX, U.K (e-mail: tughrul.arslan@ed.ac.uk).

Moataz Ahmed is from the SDAIA-KFUPM Joint Research Center for Artificial Intelligence (JRCAI) & Information and Computer Science Department, King Fahd University of Petroleum & Minerals (KFUPM), Dhahran, 31261, Saudi Arabia (e-mail: moataz@kfupm.edu.sa).

be recorded using two main techniques: invasive intramuscular EMG and non-invasive surface EMG. Intramuscular EMG uses needle electrodes inserted into the muscle, while surface EMG offers a painless, non-invasive alternative. However, sEMG is more prone to noise than intramuscular recordings because the signal must pass through skin and fat layers, which introduces Gaussian noise and impedance that can distort the signal's integrity [6]. The EMG signal denoising is a crucial part of utilizing them for patient health monitoring and decision-support.

Digital Twin (DT) technology, a cornerstone of ICT advancement in Healthcare 4.0 (H4.0), offers a transformative solution for improving patient healthcare [7], [8]. By creating a real-time virtual replica of a patient's musculoskeletal system, DT enables continuous, non-invasive monitoring using surface EMG signals. These signals, once denoised and processed, provide critical insights into muscle function, fatigue, and neuromuscular health. DT systems can integrate EMG data with AI models to detect early signs of disorders, personalize rehabilitation, and simulate patient-specific outcomes [9]. This integration of EMG with DT allows healthcare providers to shift from reactive to proactive care. Clinicians can remotely assess patient conditions, optimize therapy plans, and monitor progress over time without requiring frequent doctor visits. A digital extension of the patient, the DT reduces healthcare costs, enhances accessibility, and supports long-term management of MSDs through intelligent, data-driven interventions. Unlike conventional monitoring tools, it is a dynamic, continuously evolving model that assimilates each new EMG data point to maintain a precise, personalized digital replica of the patient's physiological state. Fig. 1 provides a generic representation of building a DT model.

AI serves as the analytical backbone of DT systems. While DTs provide a continuously evolving digital representation of the patient, AI models enhance the twin with the ability to learn from data, recognize subtle neuromuscular patterns, and predict emerging conditions [10]. In the context of EMG-based DTs, ML and DL algorithms transform raw and denoised signals into clinically meaningful digital states and the identification of abnormal patterns. AI also facilitates personalization by adapting the DT model to individual variability, ensuring that the twin reflects not only generalized musculoskeletal functions but also the patient's unique physiological profile [10], [11]. This fusion of DT and AI establishes a proactive, intelligence-driven healthcare framework capable of supporting continuous monitoring, personalized rehabilitation, and informed clinical decision-making [12].

A. Research Background

Digital Twins (DTs) are instantiated from the parameters of their physical counterparts. Therefore, accurate, continuous sensing is fundamental to building a faithful model. Sensors constitute the first stage of data acquisition for any DT. For a human DT, wearable sensors offer a clear advantage over alternative methods [13]. Implantable sensors represent another option: by operating inside the body, they can continuously record and stream clinically relevant vital data, e.g. blood glucose [14], and thus exploit the real-time capabilities of DTs. However, implants are invasive, often more expensive, and harder to maintain, which can limit their feasibility and scalability across patient populations. In contrast, wearable devices provide similarly continuous monitoring while being non-invasive, easier to deploy, and more cost-effective, making them highly suitable for DT-driven healthcare workflows [15], [16]. Moreover, wearables are essential enablers of the Internet of Things (IoT) within the DT ecosystem, allowing seamless persistent communication among all devices involved in constructing and maintaining the twin [17].

Among the various biosignals acquired through wearable sensing, EMG has gathered significant attention for its ability to capture neuromuscular activity relevant to motor function and rehabilitation [18]. Researchers have explored EMG for applications such as gesture recognition, muscle fatigue analysis, and activity classification. In recent years, Machine Learning (ML) and Deep Learning (DL) have gained prominence in biomedical signal analysis [19], including EMG interpretation. ML methods are either supervised, using labeled data to build models, or unsupervised, finding patterns without labels. DL automates the full process, learning features and models directly from raw data through multilayer networks, removing the need for manual feature extraction. The system predicts the likelihood of stroke occurrence based on real-time EMG biosignals during daily activities.

In a recent research, an IoT-based device was presented that monitors EMG signals using wearable sensors and cloud analytics [20]. The device analyzes muscle activity with ML and sends real-time alerts for abnormalities, enabling continuous, remote monitoring and improved neuromuscular care. In [21], the author proposed an improved EMG detection method (FM-ALED) using energy-based features and CFAR refinement. It achieved lower error rates than existing methods, with error probabilities as low as 0.0140 on synthetic data and strong performance on real signals from healthy and Parkinson subjects. In [22], a muscle rehabilitation monitoring system using spatiotemporal EMG signal analysis is proposed. Through experiments with different joint angles and incorrect postures, clear EMG features changes were observed. Notably, zero-cross rate and median frequency showed >0.8 correlation for fatigue detection, with zero-cross being more efficient computationally. The authors of [23] developed a real-time wearable EMG monitoring system using flexible dry electrodes and an adaptive SVM classifier. The system achieved 92% accuracy in classifying six arm movements and demonstrated stable signal quality across different skin conditions, highlighting its suitability for practical rehabilitation and assistive applications.

A flexible, textile-based dry electrode for surface EMG acquisition, integrated into a wearable sleeve. The system maintained signal quality comparable to gel electrodes and achieved over 90% classification accuracy for hand gestures using ML, demonstrating its potential for long-term, comfortable EMG monitoring in wearable applications [24]. The authors elaborated in depth on the use of ML and DL in identifying abnormal neuromuscular patterns indicative of stroke risk, enabling early intervention without relying on imaging techniques [19]. The work in [25] discusses in depth the ML and

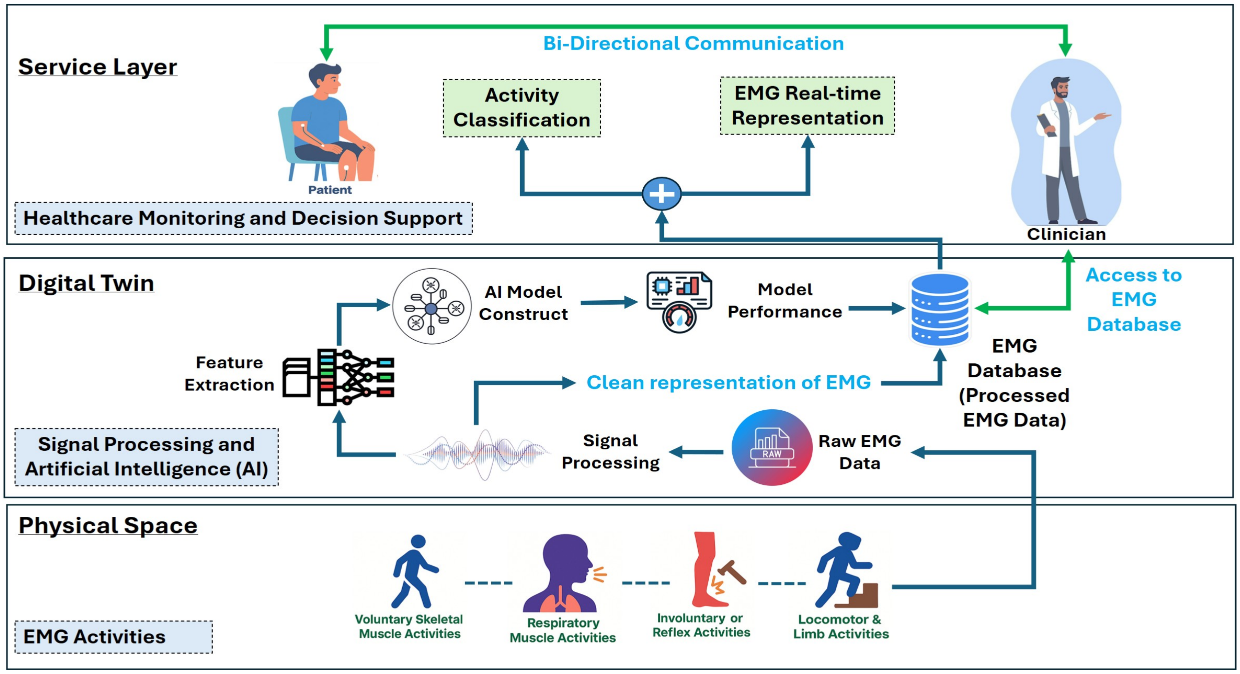


Fig. 1: Foundational process for EMG-driven (DT) development: The creation pipeline starts with the acquisition of patient EMG signals, which are then denoised and refined through feature extraction. These cleaned signals are mapped into the digital space, where AI models are trained to accurately represent underlying physiological activities. Once established, the DT enables real-time activity recognition, supports continuous monitoring, and facilitates interactive communication between patients and healthcare providers

DL models for the interpretation of the EMG signals. The authors of [26] proposed a hybrid transformer-based architecture, TraHGR, for hand gesture recognition. It employs two parallel processing pathways followed by a fusion center with a linear integration layer, enhancing robustness and adaptability across varying conditions. A stacking ensemble-learning model, the Convolutional Vision Transformer (CviT), was proposed in [27] for EMG signal classification. The approach incorporates EMG signal fusion with parallel training and achieved 80.2% accuracy on the NinaPro DB2 dataset. The work in [28] presents a comparative analysis of ML algorithms for EMG-based prosthetic arm control. Four classifiers of SVM, KNN, Logistic Regression, and Decision Tree were evaluated for multiclass classification. SVM achieved the highest accuracy (83%), followed by KNN (77%), Logistic Regression (75%), and Decision Tree (74%).

B. Research Novelty

Following are the contribution of this research toward holistic human DT model.

1) A pilot study presenting an AI-enabled EMG DT framework for continuous neuromuscular activity monitoring and decision-support readiness, serving as a foundational component for future clinical integration.
2) Supervised and semi-supervised learning enhanced with Gaussian noise based-feature augmentation is employed to strengthen the reliability of EMG classification. The approach supports binary classification, which distinguishes active from inactive muscle states, and multi-class classification, which accurately differentiates between seven physical activities. This layered classification strategy ensures both baseline detection and fine-grained activity recognition within the proposed EMG DT model.
3) An innovative feature engineering and recursive optimization framework is developed to systematically identify the most effective Machine Learning (ML) and Deep Learning (DL) algorithms for EMG-based decision support. By iteratively refining feature representations and model parameters, the DT achieves improved adaptability, robustness, and decision-support relevance across diverse patient conditions.

II. Proposed AI-Enabled Digital Twin Model for EMG-Based Patient Monitoring

The Fig. 2 illustrates the architecture of the proposed surface EMG DT developed for patient monitoring and decision support analysis. The EMG DT is designed as a patient- specific virtual replica that continuously mirrors neuromuscular activity by integrating acquisition hardware, signal pre-processing, intelligent analytics, and decision-support interfaces into a single framework.

Signal Acquisition and Pre-processing: The DT begins with the acquisition of EMG signals using surface electrodes connected to instrumentation amplifiers. The raw signals are pre-processed through offset removal, denoising, wavelet decomposition, and digital filtering. Additional steps, such as feature extraction, ensure that the signals are transformed into structured data suitable for modeling.

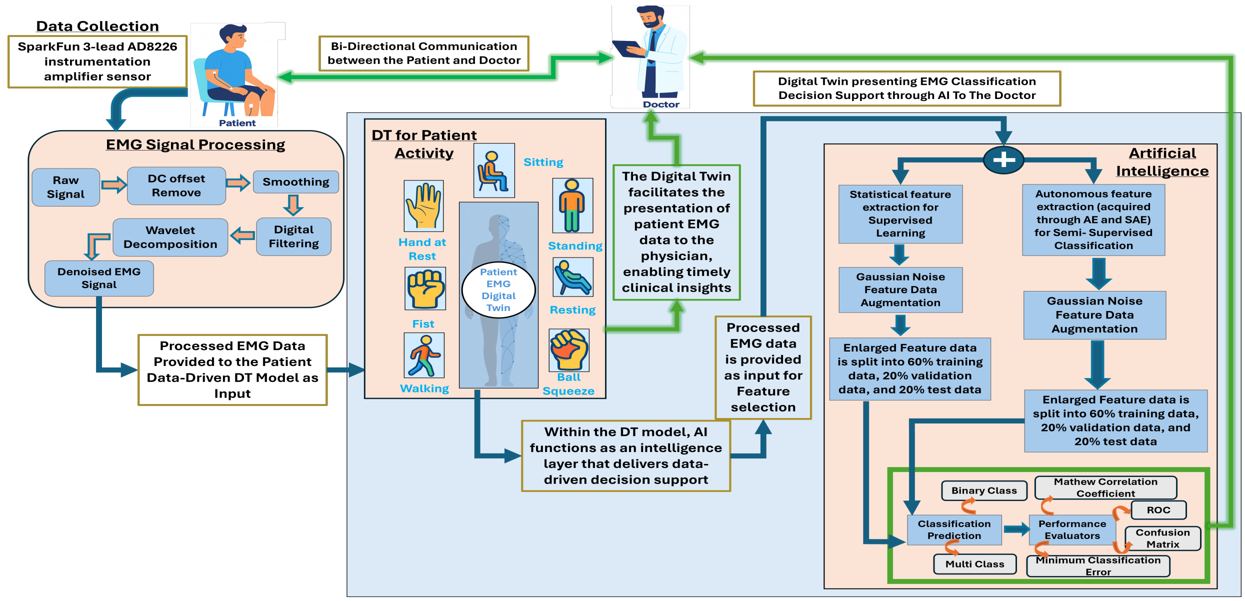


Fig. 2: Conceptual AI-enabled EMG DT framework illustrating signal acquisition, intelligent activity modeling, and decision support: The workflow shows how signals are acquired, processed, and used for activity modelling, AI-driven classification decision support.

Activity Modeling and AI-Enabled Intelligence Layer: The pre-processed EMG signals are integrated into the DT environment, where they are mapped into patient activity states (e.g., walking, sitting, standing, hand movements). At the core of the DT lies an AI-enabled intelligence layer, composed of supervised and semi-supervised adaptive learning models. These models perform feature extraction, data augmentation with Gaussian noise, and both binary and multi-class classification. This layer acts as the inference engine of the DT, continuously refining activity recognition and maintaining robustness against noise and inter-subject variability. To maintain the physiological integrity of non-stationary EMG signals within the DT, data augmentation is applied at the feature level rather than the raw signal or image level, ensuring robustness to variability while avoiding distortion of underlying neuromuscular characteristics.

In the proposed manuscript, the supervised and semi-supervised feature extraction approaches are presented as parallel and independent pipelines rather than as a unified feature fusion framework. Statistical features and autonomously learned features obtained via AE/SAE are each evaluated separately, with their respective classifiers trained and tested independently to assess comparative performance. The intention of this design is to analyze how manually engineered features and automatically learned latent representations performed under identical experimental conditions, rather than to combine them as joint inputs to a single classifier. Consequently, the study does not aim to merge or fuse features from different learning paradigms, but instead treats them as alternative representations within the AI-enabled DT framework, each following its own training strategy and classification.

Digital Twin (DT) Synchronization: By continuously integrating new EMG segments, the DT maintains a living and adaptive digital replica of the patient's neuromuscular system. Classifiers are not treated as independent predictors but as embedded intelligence modules that evolve with each new data stream, keeping the DT synchronized with the patient's physiological state in real time.

Decision-Support and Bi-Directional Interface: The DT's last part connects activity classification to a bidirectional interface. The framework is intended to provide physician-interpretable, AI-driven activity insights that show how patient monitoring data may be examined and contextualized. Furthermore, the DT facilitates conceptual physician feedback methods designed to improve monitoring tactics in the digital model. This guarantees that the DT is both decision support-ready and indicative of the patient's condition, providing a basis for upcoming healthcare decision-making processes.

III. EMG Data & Signal Denoising

The sEMG signals were integrated from an external dataset to represent muscle activity associated with various physical tasks. The sEMG signals were obtained from the PIFv3 dataset, recorded with a SparkFun 3-lead AD8226 instrumentation amplifier sensor from 32 participants across diverse demographics [29]. The dataset includes raw EMG traces (EMGRaw) and derived features such as EMGRMS, and EMGMAV. While the archival metadata does not state the original sampling rate, standard usage of the AD8226 in multi-model wearable systems suggests it is approximately 1000Hz, which is sufficient for capturing muscle activation bands from 20Hz to 450Hz.

Effective signal pre-processing is essential to ensure the reliability of EMG and respiration data for feature extraction and classification. Both signals are prone to noise, artifacts, and baseline drifts, which can distort physiological information. Fig. 3 provide the outline for the signal processing steps applied to denoise EMG data. In [25], the authors provides a discussion on EMG signal processing and the importance of denoising raw sensor data. In [30], the authors present signal processing for their proposed Respiration DT framework called ”ResDT”.

To enhance signal quality, various digital filters were evaluated for their effectiveness in denoising EMG and respiration signals. This subsection presents a comparative analysis of filters based on their ability to preserve key signal characteristics while minimizing noise, guiding the selection of optimal filtering strategies for each entity.

The activities provided in the dataset are Sitting, Standing, Walking, Relax, Stress Ball, Hand at Rest, and Fist. The EMG dataset was annotated with activity labels corresponding to each timestamp during acquisition. During EMG signal acquisition, each data point was time-stamped, and the corresponding physical activity was recorded in parallel. This predefined mapping between timestamps and activities eliminates the need for activity recognition or detection algorithms. Instead, the EMG data is directly segmented based on these timestamps, enabling targeted feature extraction for each specific activity, such as standing, walking, or sitting. This approach ensures precise alignment between the physiological signals and the performed activities, facilitating focused analysis and interpretation of muscle activation patterns relevant to each task.

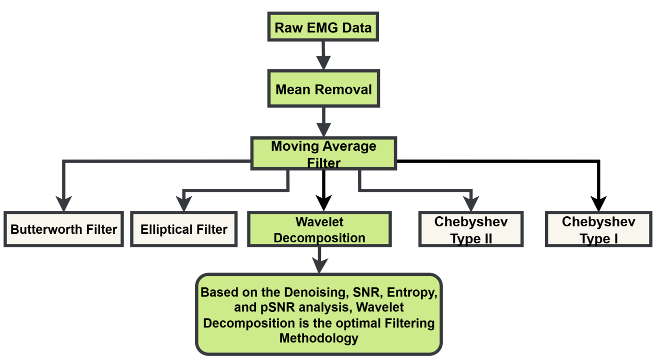


Fig. 3: EMG Pre-processing Pipeline and Filter Evaluation for Denoising

The Table I provides parametric analysis for multiple digital filters. The comparative analysis confirms Wavelet Decomposition as the optimal EMG denoising technique, achieving the highest SNR (26.50 dB), maximum entropy (4.9), and the least negative pSNR (-14.89 dB). These metrics collectively indicate superior noise suppression, enhanced information content, and minimal signal distortion compared to conventional filters like Butterworth, Elliptical, and Chebyshev. The raw EMG signal denoising representation is provided in Fig. 4 to Fig. 7. The population-level wavelet denoising findings for 32 participants are shown in Table II, with narrow 95% confidence intervals and a mean SNR of 26.5 ± 3.2 dB, indicating consistent performance throughout the cohort. The distribution of post-denoising SNR values is further shown in Figure 8, which verifies the robustness of the wavelet-based denoising technique by showing little inter-subject variability and no noticeable outliers.

Wavelet Decomposition excels due to its multi-resolution analysis capability, enabling it to decompose signals across various frequency bands with adaptive time-frequency localization. This is critical for EMG signals, which are inherently non-stationary with transient, multi-frequency characteristics. Unlike fixed-parameter linear filters, wavelets can isolate noise while preserving essential physiological information such as muscle activation bursts. Thus, wavelet decomposition not only enhances the signal quality quantitatively but also maintains the morphological integrity of the EMG signal, making it the most robust and physiologically reliable filtering method for biomedical applications.

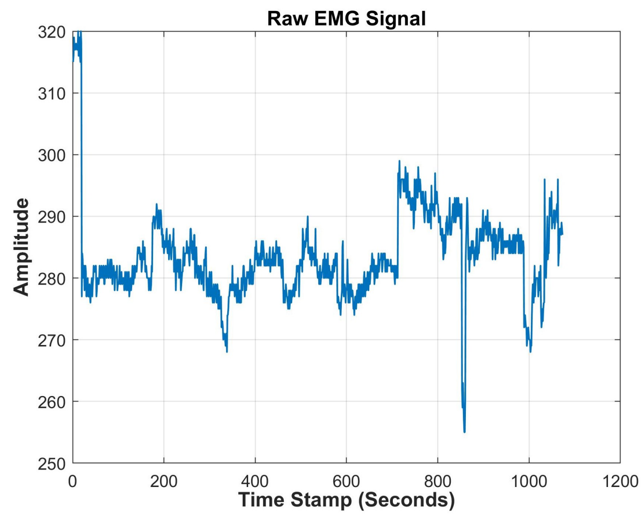


Fig. 4: Raw Multi Activity Surface EMG Signal

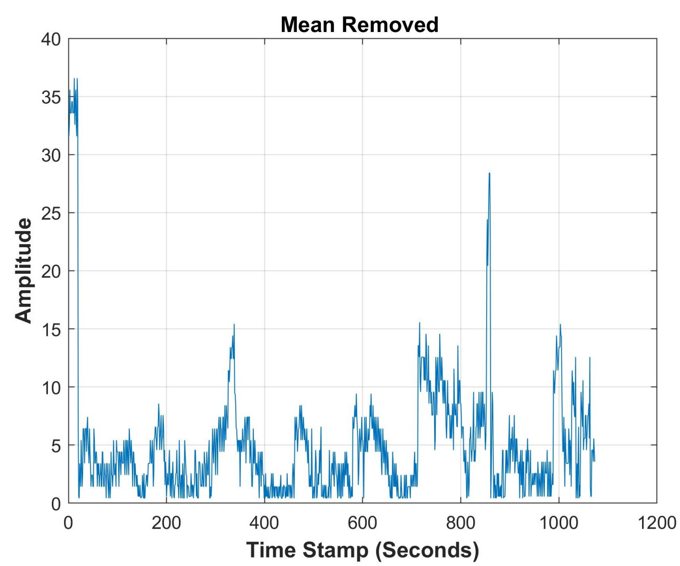


Fig. 5: DC-offset removed from the EMG signal

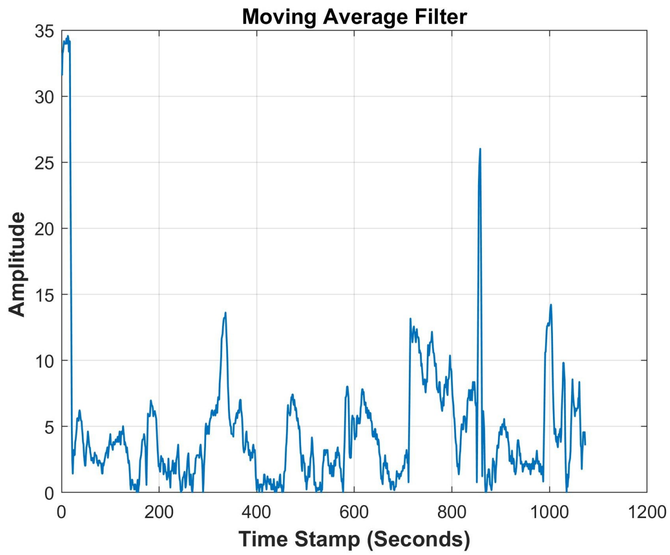


Fig. 6: Smoothing through Moving Average Filter

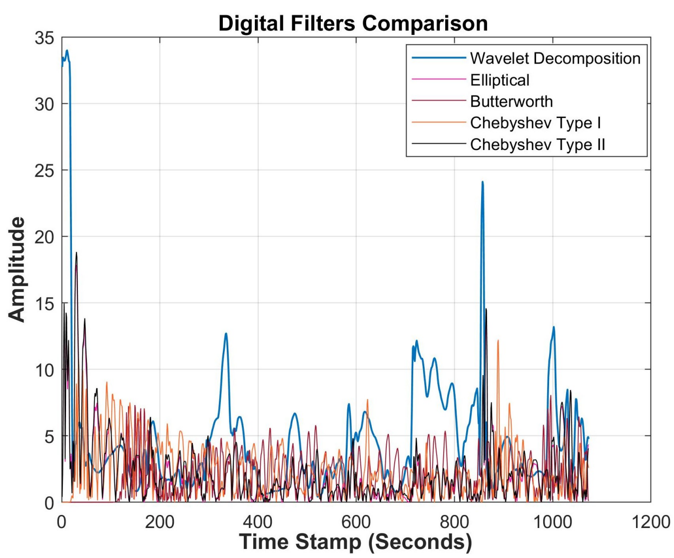


Fig. 7: EMG Signal Denoising: Digital Filters vs. Wavelet Decomposition

TABLE I: Comparison of Digital Filtering Techniques for EMG Signal Denoising: SNR, Entropy, and pSNR Analysis for a single subject

Filter Type	SNR-Raw (dB)	Entropy-Raw	SNR-Processed (dB)	Entropy-Processed	pSNR (dB)
Elliptical	0.03	3.57	9.31	3.80	-21.59
Butterworth	-0.16	3.56	15.45	3.71	-19.20
Chebyshev Type I	-0.15	3.57	12.80	3.95	-20.50
Chebyshev Type II	-0.16	3.57	10.33	3.06	-21.10
Wavelet Decomposition	**0.13**	**3.57**	**26.50**	**4.9**	**-14.89**

TABLE II: Population-level wavelet-based EMG denoising performance across 32 subjects. Values are reported as mean ± standard deviation with 95% confidence intervals.

Metric	Mean ± Std	95% CI
SNR (dB)	26.5 ± 3.2	[25.4, 27.6]
Entropy	4.90 ± 0.4	[4.75, 5.05]
pSNR (dB)	-14.89 ± 1.6	[-15.4, -14.3]

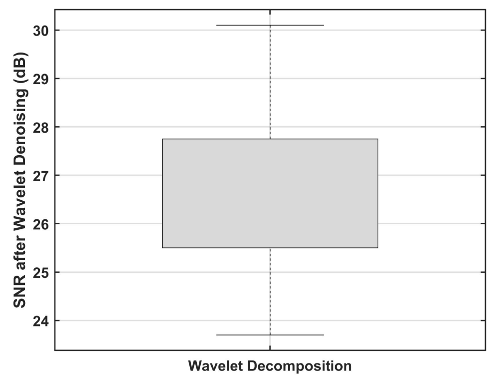


Fig. 8: Distribution of wavelet-based EMG denoising performance across 32 subjects shown using a boxplot of post-denoising SNR values

IV. Gaussian-Based Feature Augmentation

This section introduces a physiological constraint, feature-level data augmentation methodology tailored for EMG DT modeling. The methods enhance training data diversity and robustness while preserving the neuromuscular characteristics of inherently non-stationary EMG signals. Unlike raw signal or image-level augmentation, the proposed approach operates directly on denoised and segmented EMG feature vectors. Low variance, zero mean Gaussian noise is injected to introduce controlled variability that reflects realistic inter and intra-subject differences without altering meaningful muscle activation patterns.

The augmentation process is formally defined and applied only to the training data within the DT learning pipeline to prevent data leakage. Data augmentation is a crucial strategy to overcome the limitations of small and imbalanced EMG datasets, often encountered in biomedical signal analysis. By generating synthetic data, augmentation enhances classifier robustness, accuracy, and generalization [31]. In this research work, the feature data augmentation is applied to the statistical features extracted from EMG signals, aiming to improve classification performance in scenarios constrained by limited experimental data availability. While prior studies like [32] employed image-based augmentation to expand EEG datasets, this research focuses on time-series feature augmentation tailored to EMG assessments. A detailed performance evaluation demonstrates that augmenting feature data significantly improves model reliability and classification accuracy. Additionally, authors of [33], [34] utilized similar feature data augmentation techniques for enlarging the feature data for cerebral blood flow and stroke classification analysis.

In image processing, data augmentation typically involves geometric transformations like scaling, rotation, and shifting, or adding noise to the data. However, applying such geometric transformations to time-series data is problematic because they can disrupt the temporal structure and alter essential frequency characteristics, rendering them ineffective for time-domain features. Conversely, noise injection remains a viable augmentation strategy for respiration data. Techniques such as Gaussian, Pepper, Salt, and Poisson noise can be used to create synthetic samples. Yet, due to the random and non-stationary nature of EMG signals, noise types like Salt, Pepper, and Poisson may introduce localized distortions that can degrade the quality of the augmented feature data [32].

Feature-level data augmentation is adopted in this work due to the non-stationary and physiologically sensitive nature of time-series EMG signals. Applying augmentation directly at the raw signal level, such as temporal scaling, shifting, or high-intensity noise injection, can distort motor unit activation patterns and modify the inherent time frequency characteristics of EMG, resulting in physiologically unrealistic samples. Likewise, image-based augmentation techniques are not well suited for EMG analysis, as they require transforming one dimensional EMG signals into image representations, which introduces additional abstraction and potential artifacts that are unrelated to actual neuromuscular activity. Instead, feature-level augmentation is performed on denoised and segmented EMG representations that already capture clinically meaningful muscle activation characteristics. The addition of low-variance Gaussian noise to statistical and later feature vectors enable the generation of synthetic samples that reflect natural inter and intra-subject variability while maintaining class-discriminative information. This approach improves model robustness and generalization and aligns well with the objectives of the proposed AI-enabled EMG DT framework.

In this research, Gaussian noise is applied at the feature level (not on raw EMG), to create synthetic feature data. Gaussian noise mean μ is kept at 0, whereas, the variances σ of 0.01 and 0.02 are analyzed. For each original feature vector $\mathbf{x}$, m augmented copies were generated according to:

$$\mathbf{x}_{\text{aug}}^{(r)} = \mathbf{x} + \boldsymbol{\epsilon}^{(r)}, \quad r = 1, \ldots, m, \tag{1}$$

where each noise vector $\boldsymbol{\epsilon}^{(r)}$ was independently sampled from a zero-mean Gaussian distribution, $\boldsymbol{\epsilon}^{(r)} \sim \mathcal{N}(\mathbf{0}, \sigma^2\mathbf{I})$.

To prevent data leakage and ensure unbiased performance evaluation, Gaussian noise augmentation was applied exclusively to the training set after dataset shuffling and partitioning. The dataset was split into 60% training, 20% validation, and 20% testing subsets, with 5-fold cross-validation performed on the validation set.

V. Classification of EMG-Based Activities

In the proposed AI-enabled EMG DT framework, classification models function as embedded inference engines that map processed EMG feature representations to discrete physiological activity states. This classification layer constitutes the intelligence core of the DT, enabling continuous synchronization between the physical subject and its digital counterpart. A two-level classification strategy is implemented to support both baseline and fine-grained neuromuscular assessment. Binary classification distinguishes inactive and active muscle states, while multi-class classification identifies 7 distinct physical activities. Supervised and semi-supervised learning models are integrated into this inference layer to ensure robustness, adaptability, and reproducibility under varying signal conditions.

The AI execution and software workload were performed using MATLAB 2024b and Python. The activities under consideration from the dataset [29] are Sitting, Standing, Walking, Relax, Stress Ball, Hand at Rest, Fist.

1) **Binary class classification:** This classification distinguishes between the body at rest and the body in motion based on EMG signal activation. The EMG activities ”Relax” and ”Hand at Rest” are categorized as the body at rest. In contrast, the activities ”Sitting”, ”Standing”, ”Walking”, ”Stress Ball”, and ”Fist” are categorized as body in motion or EMG active. The training data is labeled as 0 for No-EMG activity and 1 for EMG activity.
2) **Multi-class classification:** This classification involves discriminating among the seven distinct EMG activity classes. The training data is labeled as 1 for Standing, 2 for Sitting, 3 for Walking, 4 for Relax, 5 for Stress Ball, 6 for Hand at Rest, and 7 for Fist. Each class corresponds to a specific physiological state or movement, allowing for a detailed characterization of body posture and activity based on EMG signal patterns.

A. Statistical Feature Supervised Classification

In statistical feature classification, the selected features are mean (μ), standard deviation (σ), quartile deviation ($\daleth$), range (R), skewness (S), and kurtosis (K) [33], [34]. The features are not extracted directly from the pre-processed EMG signal. Instead, each EMG signal is associated with time stamps corresponding to different activities. The signal is first segmented based on these time stamps, and then statistical features are extracted from each segmented portion representing a specific activity.

These statistical metrics capture essential aspects of the EMG signal, such as amplitude variability, signal dispersion, asymmetry, and sharpness, which are crucial for distinguishing between different muscle contractions, activity levels, or physiological states. By converting the raw EMG signal into these features over sliding windows or epochs, the high-dimensional time-series data is transformed into a compact and structured form suitable for input into classification models like Decision Tree, Support Vector Machine (SVM), Naive Bayes, Ensemble, K-Nearest Neighbors (KNN), Discriminant Analysis, or Neural Networks (NN). This study adopted a progressive feature selection strategy, beginning with the mean and standard deviation, which resulted in binary and multiclass accuracies of 68.5% and 64.1%, respectively. When range and kurtosis were added, the accuracies increased to 77.5% and 76.8%. The best outcomes were ultimately achieved using all six statistical features, as reported in this research.

The different families of classification models are trained on the new synthetic feature dataset. The entire dataset is first shuffled and then split into 60% for training, 20% for validation, and 20% for testing. The validation process further utilizes a 5-fold cross-validation approach. The Table IV and Table V provide the binary class and multi-class classification of EMG signals with Gaussian noise feature data augmentation with variance 0.01 and 0.02.

1) Fine KNN Classification Principle: The Fine KNN is a distance-based non-parametric classification algorithm that assigns a class label to a test sample based on the labels of its nearest neighbors in the feature space. In this research, the Fine KNN corresponds to a small value of k (typically $k = 1$ in MATLAB), combined with the Euclidean distance metric, resulting in a highly localized and fine-grained decision boundary.

In the framework presented in Fig. 2, the Fine KNN algorithm is part of the AI-enabled intelligence layer that follows EMG signal acquisition, pre-processing, and statistical feature extraction. At this stage, Fine KNN is employed as a supervised classifier to map the extracted feature vectors into discrete activity classes. These classification results are used within the framework to support decision-making for activity assessment.

Algorithm 1 Fine KNN for EMG Activity Classification

Input: Pre-processed EMG signal segments with class labels (binary or 7-class)
Feature Extraction:
for each EMG segment **do**
  Compute feature vector $\{\mu, \sigma, QD, R, S, K\}$
end for
Optional Data Augmentation:
Add Gaussian noise to feature vectors with variance 0.01 or 0.02
Dataset Partitioning:
Split data into 60% training, 20% validation, and 20% testing sets
Apply 5-fold cross-validation on the validation set
Training (Fine KNN):
Select Euclidean distance metric
Set a small value of k
Store training feature vectors and corresponding labels
Inference:
for each test feature vector **do**
  Compute distances to all training vectors
  Select the k nearest neighbors
  Assign class label using majority voting
end for
Output:
Predicted class labels and performance evaluation using confusion matrix and ROC curve (for binary classification) =0

The use of a small value of k enables the Fine KNN classifier to focus on localized neighborhood structures in the EMG feature space, making it well-suited for scenarios where EMG activity classes demonstrate locally separable feature characteristics. Although small k values increase sensitivity to noise and outliers, this limitation is mitigated in the proposed framework through effective EMG signal denoising and Gaussian noise-based feature data augmentation.

Each EMG segment is represented by a low-dimensional statistical feature vector

$$\mathbf{x} \in \mathbb{R}^d, \tag{2}$$

where $d = 6$ corresponds to the extracted features: mean, standard deviation, quartile deviation, range, skewness, and kurtosis.

Given a test feature vector $\mathbf{x}_{\text{test}}$, the Euclidean distance to each training sample $\mathbf{x}_i$ is computed as

$$d(\mathbf{x}_{\text{test}}, \mathbf{x}_i) = \sqrt{\sum_{j=1}^{d} \left(x_{\text{test},j} - x_{i,j}\right)^2}. \tag{3}$$

The k nearest training samples are identified based on the minimum distance values. The predicted class label $\hat{y}$ is then assigned using a majority voting scheme among these neighbors. For weighted KNN, closer neighbors contribute higher influence to the final decision.

For binary classification, the output label is defined as $\hat{y} \in \{0, 1\}$, corresponding to inactive and active EMG states, respectively. For multi-class classification, the output label is defined as:

$$\hat{y} \in \{1, 2, \ldots, 7\}, \tag{4}$$

representing the seven distinct physical activities considered in this study.

Feature importance was analyzed using permutation importance and SHAP to evaluate the effectiveness of the selected statistical features. Permutation importance quantified the global contribution of each feature by measuring performance degradation when features were randomly permuted, while SHAP provided global and local explanations of feature contributions to KNN predictions. Both methods consistently identify dispersion-related features, particularly range, quartile deviation, and standard deviation, as the most influential for the classification task. In contrast, the mean feature exhibits a negligible impact on model performance. This confirms that classification performance is driven by statistically meaningful variability descriptors and validates the importance of the selected feature set. The Fig. 9 and Fig. 10 provide quantitative evidence of feature effectiveness by visualizing both individual and global SHAP-based feature contributions. The permutation values for statistical features were Range (0.25), Quartile Deviation (0.16), Standard Deviation (0.10), Kurtosis (0.09), Skewness (0.03), and Mean (0.1).

2) Classification Analysis: The algorithms of Fine KNN provide the best classification accuracies of 94.6% and 91.6% for binary and multi-class, respectively, with Gaussian noise feature data augmentation of 0.01. However, increasing the Gaussian noise variance level from 0.01 to 0.02 led to a noticeable drop in classification accuracy. This decline is likely due to the higher noise introducing greater variability in the features, which reduces the model's ability to effectively

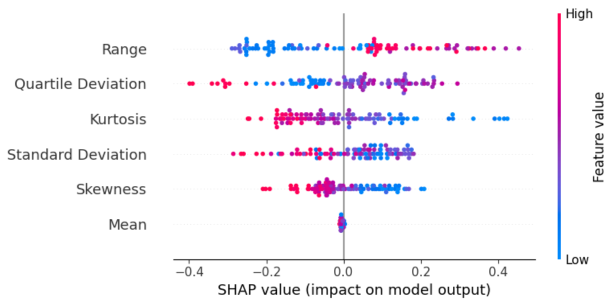


Fig. 9: SHAP summary plot showing the distribution and direction of feature contributions across individual samples.

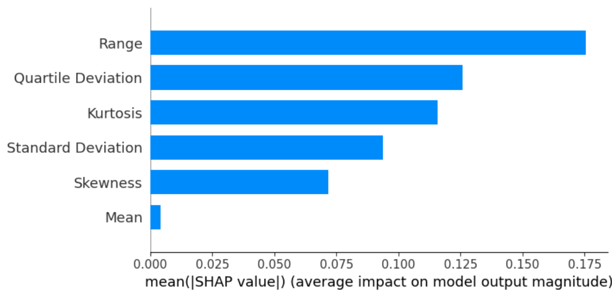


Fig. 10: Mean absolute SHAP values illustrating the global importance ranking of statistical features in the KNN classifier.

separate the classes. As a result, the model struggles more with accurate class identification, leading to overall lower performance.

The Fig. 11 represents the confusion matrix of Fine KNN binary class classification. The Fig. 12 provides a Receiver-Operating Characteristic (ROC) curve for binary class classification. Additionally, the minimum classification error for Fine KNN is provided in Fig. 13. For multiclass performance evaluation, Fig. 14 illustrates the confusion matrix for the Fine KNN model, while Fig. 15 presents the minimum classification error achieved across the multiclass setup. The Table III provides performance evaluation for binary and multiclass classification. The observed performance gains across multiple classifiers further validate the role of feature-level augmentation in improving model generalization.

Feature-level data augmentation improves classification performance by increasing the effective size and diversity of the training dataset while preserving the physiological characteristics of EMG signals. The addition of low-variance Gaussian noise introduces controlled variability within each class, which enhances intra-class representation and improves class separability in the feature space. This leads to more stable decision boundaries, reduced overfitting, and improved generalization, particularly for small imbalanced datasets. Consequently, the Fine KNN and SAE have benefited from denser neighborhood structures and more robust latent representations, resulting in higher classification accuracy. The authors of [35]–[37] worked on improving classification accuracy using data augmentation on small data sets, observing noise injection techniques to prevent overfitting and improve the accuracy of predictions.

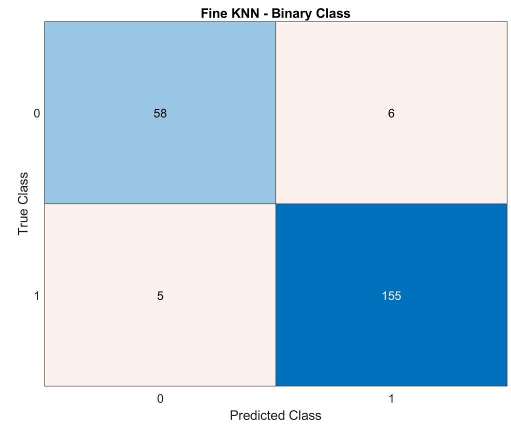


Fig. 11: Statistical Feature Based Binary Class Classification Confusion Matrix with Fine KNN

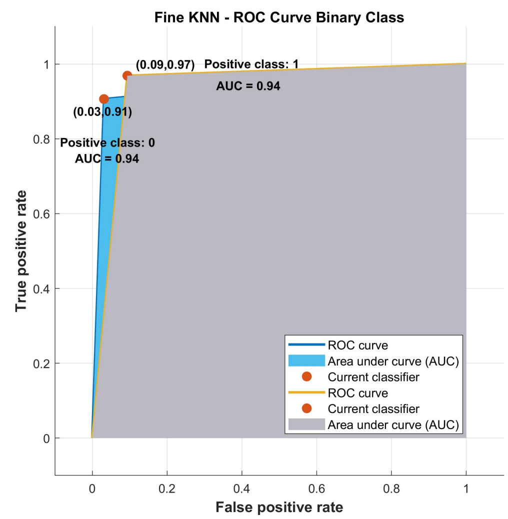


Fig. 12: Statistical Feature Binary Class Classification ROC with Fine KNN

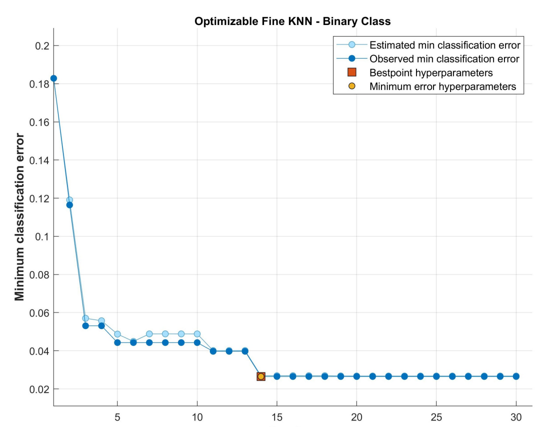


Fig. 13: Optimizable Fine KNN in Binary Class Classification

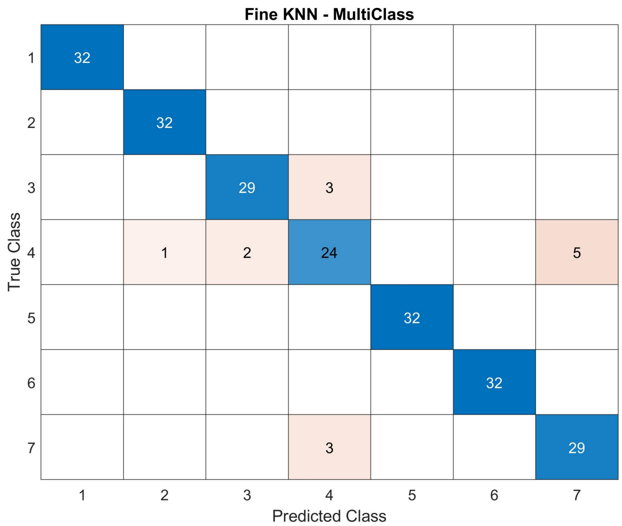


Fig. 14: Statistical Feature Based Multi-class Classification Confusion Matrix with Fine KNN

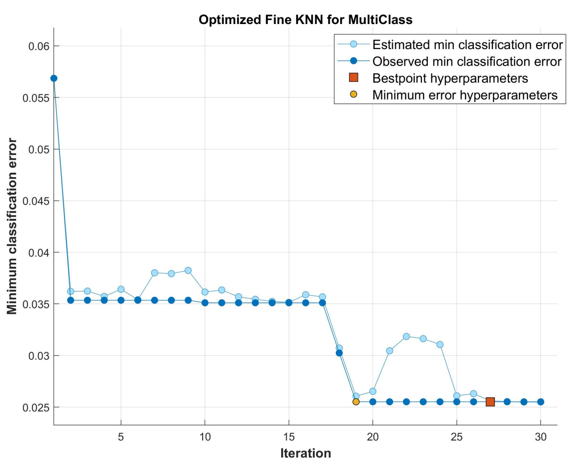


Fig. 15: Optimizable Fine KNN in Binary Class Classification

TABLE III: Classification Metrics for Fine KNN – Binary and MultiClass

Mode	Class	Precision	Recall	F1 Score
Binary	Class 0	0.92	0.90	0.91
	Class 1	0.96	0.96	0.96
MultiClass	Class 1	0.96	1.00	0.98
	Class 2	0.94	1.00	0.96
	Class 3	0.90	0.90	0.90
	Class 4	0.88	0.75	0.81
	Class 5	1.00	1.00	1.00
	Class 6	1.00	1.00	1.00
	Class 7	0.85	0.90	0.87

TABLE IV: Supervised Binary Class Classification on Statistical Features Enhanced by Gaussian Noise

Groups	Algorithm	Statistical feature with 0.01 Gaussian	Statistical feature with 0.02 Gaussian
Decision Tree	Fine Tree	88.74	77.86
	Medium Tree	85.26	80.34
	Coarse Tree	91.04	77.66
Discriminant Analysis	Linear Discriminant	79.64	70.96
	Quadratic Discriminant	78.16	72.94
Naïve Bayes	Gaussian Naïve Bayes	81.24	72.06
	Kernel Naïve Bayes	81.06	80.74
SVM	Linear SVM	88.44	71.56
	Quadratic SVM	83.96	77.14
	Cubic SVM	89.64	72.86
	Fine Gaussian SVM	83.46	69.24
	Medium Gaussian SVM	87.94	74.66
	Coarse Gaussian SVM	83.96	70.54
KNN	Fine KNN	**94.6**	**88.3**
	Medium KNN	88.86	78.24
	Coarse KNN	88.84	70.26
	Cosine KNN	91.74	75.96
	Cubic KNN	88.86	76.94
	Weighted KNN	91.14	80.76
Ensemble	Ensemble Boosted Tree	77.94	69.86
	Ensemble Bagged Tree	87.56	83.24
	Ensemble Subspace Discriminant	81.44	69.46
	Ensemble Subspace KNN	88.84	80.16
Neural Network	Narrow Neural Network	91.54	81.16
	Medium Neural Network	88.46	80.34
	Wide Neural Network	90.14	77.86

Additionally, the Matthew Correlation Coefficient (MCC) [38] is presented for binary class classification through equation 5. The MCC is 0.879 for the statistical feature-based binary class classification with Fine KNN.

$$MCC = \frac{TP{\cdot}TN - FP{\cdot}FN}{\sqrt{(TP+FP){\cdot}(TP+FN){\cdot}(TN+FP){\cdot}(TN+FN)}} \tag{5}$$

TABLE V: Supervised Multi-class Classification on Statistical Features Enhanced by Gaussian Noise

Groups	Algorithm	Statistical feature with 0.01 Gaussian	Statistical feature with 0.02 Gaussian
Decision Tree	Fine Tree	90.0	76.62
	Medium Tree	84.02	81.58
	Coarse Tree	92.28	76.42
Discriminant Analysis	Linear Discriminant	80.88	69.72
	Quadratic Discriminant	76.92	74.18
Naïve Bayes	Gaussian Naïve Bayes	82.48	70.82
	Kernel Naïve Bayes	79.82	82.0
SVM	Linear SVM	89.68	70.32
	Quadratic SVM	82.72	78.38
	Cubic SVM	90.88	71.62
	Fine Gaussian SVM	82.22	70.48
	Medium Gaussian SVM	89.18	73.42
	Coarse Gaussian SVM	82.72	71.78
KNN	Fine KNN	**91.6**	**89.5**
	Medium KNN	87.62	79.48
	Coarse KNN	90.08	69.02
	Cosine KNN	92.98	74.72
	Cubic KNN	87.62	78.18
	Weighted KNN	92.38	79.52
Ensemble	Ensemble Boosted Tree	79.18	68.62
	Ensemble Bagged Tree	88.80	81.98
	Ensemble Subspace Discriminant	82.68	68.22
	Ensemble Subspace KNN	90.08	78.92
Neural Network	Narrow Neural Network	92.78	79.92
	Medium Neural Network	87.22	81.58
	Wide Neural Network	91.38	76.62

B. Autonomous Feature Semi-Supervised Classification

This study further discusses the accuracy achieved by manually extracted features using various ML and DL algorithms. However, automatic feature extraction is the preferred approach, as manually selecting relevant features can be challenging and may lead to overlooking critical underlying patterns. Automatic feature extraction not only enhances classification accuracy but also reduces the risk of overfitting compared to manual feature selection methods [39].

The AE and SAE models are employed for automatic feature extraction within the proposed AI-driven EMG DT framework. These models operate in an unsupervised manner, learning compact low-dimensional latent representations from EMG data without relying on class labels, thereby capturing intrinsic signal characteristics and underlying patterns. In the semi-supervised learning setting, the trained AE and SAE models first minimize reconstruction loss to obtain robust latent features, which are subsequently used as inputs to downstream classifiers trained with the available labeled data. To improve generalization and reduce overfitting, early stopping based on validation loss is applied during training, ensuring stable and reliable performance across both unsupervised and semi-supervised learning paradigms.

Fig. 16, Fig. 17 and Fig. 18 provides confusion matrix and ROC for binary and multiclass Medium Neural Network classification for SAE structure 32-16-32. Table VIII provides classification Metrics for the Medium Neural Network in Binary and MultiClass SAE 32-16-32.

In this research, semi-supervised EMG classification for both binary and multi-class classification using AE, and SAE for feature extraction, with architectures set up as 32-16-32, 64-32-16-32-64, and 128-64-32-16-32-64-128. Table VI provides detailed parameters for autonomous feature extraction through semi-supervised learning. The latent features extracted through these methodologies are expanded and enriched through the feature data augmentation methodology of Gaussian noise of 0.01 variance. The Table VII provides the EMG activity classification accuracies of AE and SAE. The highest classification accuracies for binary class and multi-class are provided by SAE (32-16-32) with 96.4% and 93.3%, respectively. It is important to observe that the increase in SAE complexity does not increase the classification performance.

As the complexity of SAE architectures increases, a notable decline in classification accuracy is often observed. Several factors contribute to this reduction in performance. Primarily, deeper SAEs are prone to overfitting, where the model starts capturing noise and irrelevant patterns rather than meaningful features, which severely impacts its ability to generalize to unseen data. Additionally, increasing depth introduces the vanishing gradient problem during training, limiting effective weight updates and reducing the model's learning capacity. The higher number of parameters in deeper SAEs further demands a larger volume of diverse training data to achieve reliable performance- a requirement that is often unmet, particularly in biomedical datasets like EMG, respiration, or stroke vitals signals. Excessive depth can also lead to over-compression of features, resulting in the loss of critical information necessary for accurate classification. Consequently, these limitations collectively drive the declining trend in accuracy as SAE architectures become more complex, emphasizing the need to carefully balance model depth, data availability, and task complexity to optimize performance.

The results indicate that although SAE (16-8-16) achieves competitive accuracy, SAE (32-16-32) consistently provides equal or slightly superior performance across most classifiers and both binary and multi-class scenarios. In contrast, further increasing the network depth leads to a degradation in performance, which can be attributed to overfitting and increased model complexity relative to the available EMG data. These findings suggest that SAE (32-16-32) offers an effective trade-off between representational capacity and generalization, thereby justifying its selection as the adopted architecture.

According to equation 5, the MCC for Medium Neural Network binary class classification comes out to be 0.92. Indicating a stronger correlation between the predicted and true classes compared to the Fine KNN model. This reflects excellent binary class classification performance with high reliability.

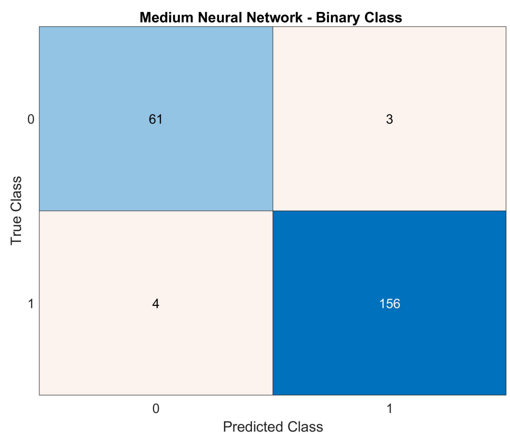


Fig. 16: Medium Neural Network Binary Class Classification of EMG activity using SAE (32-16-32)

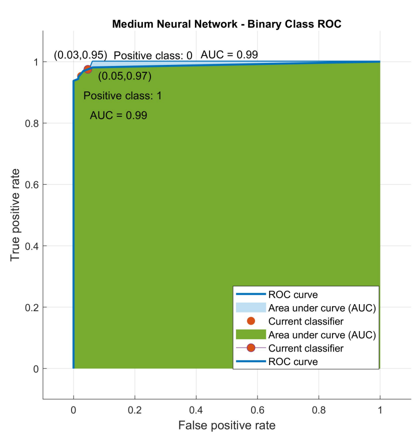


Fig. 17: Medium Neural Network ROC for Binary Class Classification of EMG activity using SAE (32-16-32)

Fig. 18: Medium Neural Network Multiclass Classification of EMG activity using SAE (32-16-32)

TABLE VIII: Classification Metrics for Medium Neural Network in Binary and MultiClass with SAE (32-16-32)

Mode	Class	Precision	Recall	F1 Score
Binary	Class 0	0.93	0.95	0.94
	Class 1	0.98	0.97	0.97
MultiClass	Class 1	0.92	0.73	0.81
	Class 2	0.96	0.96	0.96
	Class 3	0.96	0.96	0.96
	Class 4	0.93	1.00	0.96
	Class 5	0.91	1.00	0.95
	Class 6	0.93	1.00	0.96
	Class 7	0.96	0.93	0.95

A comparative analysis between statistical feature-based methods and autonomous feature extraction approaches reveals notable advantages of the latter in EMG time series classification. While statistical parameters provided respectable binary and multiclass classification accuracies of 94.6 and 91.6, respectively, with the Fine KNN algorithm, the use of autonomous feature extraction through AE and SAE yielded even higher accuracies, achieving 96.4 for binary classification while maintaining 91.6 for multiclass classification. This improvement highlights the capability of autonomous methods to uncover deeper, more abstract representations within the EMG signals that manual statistical features may overlook. Unlike statistical approaches that rely on predefined metrics, AEs and SAEs automatically learn complex patterns and relationships directly from the data, enhancing the model's ability to generalize across varying signal conditions and subjects. Furthermore, autonomous methods reduce the dependency on manual feature engineering, streamlining the classification pipeline while providing a scalable solution adaptable to different datasets. Overall, the comparative results demonstrate that autonomous feature extraction can significantly enhance classification performance, particularly in capturing the intricate dynamics of EMG signals that are critical for accurate activity recognition.

TABLE VI: Configuration Details for AE and SAE Architectures in Semi-Supervised Learning

Model	AE	SAE (32-16-32)	SAE (64-32-16-32-64)	SAE (128-64-32-16-32-64-128)
Input Shape	input_dim	num_features	num_features	num_features
Encoder Layers	52	[32, 16, 32]	[64, 32, 16, 32, 64]	[128, 64, 32, 16, 32, 64, 128]
Decoder Layers	input_dim	[16, 32, output]	[16, 32, 64, output]	[16, 32, 64, 128, output]
Encoder Activation	ReLU	ReLU	ReLU	ReLU
Decoder Activation	Linear	Linear	Linear	Linear
Loss Function	MSE	MSE	MSE	MSE
Optimizer	Adam	Adam	Adam	Adam
Epochs	25	20	30	40
Batch Size	64	32	32	16
Validation Split	20% (0.2)	20% (0.2)	20% (0.2)	20% (0.2)
Encoded Data Shape	(samples, 52)	(samples, 16)	(samples, 16)	(samples, 16)
Early Stoppage	Enabled for all models (monitored on val_loss, patience = 15)			

TABLE VII: Semi-Supervised EMG Classification Accuracies

Groups	Algorithm	AE		SAE (16-8-16)		SAE (32-16-32)		SAE (64-32-16-32-64)		SAE (128-64-32-16-32-64-128)	
		Binary Class	Multi Class	Binary Class	Multi Class	Binary Class	Multi Class	Binary Class	Multi Class	Binary Class	Multi Class
Decision Tree	Fine Tree	85.0	78.0	87	80.5	90.0	86.0	88.0	84.0	85.0	80.0
	Medium Tree	84.0	77.0	86.5	79.5	89.0	85.0	87.0	83.0	84.0	79.0
	Coarse Tree	83.0	76.0	85.8	78.5	88.0	84.0	86.0	82.0	83.0	78.0
Discriminant Analysis	Linear Discriminant	84.5	77.5	87	80	89.5	85.5	87.5	83.5	84.5	79.5
	Quadratic Discriminant	85.5	78.5	87.5	81	90.5	86.5	88.5	84.5	85.5	80.5
Naïve Bayes	Gaussian Naïve Bayes	83.5	76.5	86.8	79.8	88.5	84.5	86.5	82.5	83.5	78.5
	Kernal Naïve Bayes	84.0	77.0	85.5	78.8	89.0	85.0	87.0	83.0	84.0	79.0
SVM	Linear SVM	85.5	78.5	87.2	80.8	90.5	86.5	88.5	84.5	85.5	80.5
	Quadratic SVM	85.0	78.0	86.8	80	90.0	86.0	88.0	84.0	85.0	80.0
	Cubic SVM	84.5	77.5	86	79	89.5	85.5	87.5	83.5	84.5	79.5
	Fine Gaussian SVM	84.0	77.0	85.2	78.2	89.0	85.0	87.0	83.0	84.0	79.0
	Medium Gaussian SVM	83.5	76.5	85.8	79	88.5	84.5	86.5	82.5	83.5	78.5
	Coarse Gaussian SVM	83.0	76.0	84.8	77.8	88.0	84.0	86.0	82.0	83.0	78.0
KNN	Fine KNN	88.0	81.0	90	83.5	95.0	92.0	94.0	88.8	91.0	86.5
	Medium KNN	88.6	81.3	91	84.8	**96.4**	**93.3**	94.4	90.9	91.2	86.7
	Coarse KNN	87.5	81.0	89	83	96.0	92.9	94.0	90.7	91.0	86.5
	Cosine KNN	87.0	80.5	89.2	83.5	95.5	92.5	93.5	90.3	90.5	86.0
	Cubic KNN	87.5	80.8	89.5	84	95.8	92.8	93.8	90.6	90.8	86.2
	Weighted KNN	87.0	80.5	89	83.8	95.5	92.5	93.5	90.3	90.5	86.0
Ensemble	Ensemble Boosted Tree	84.5	77.5	87	80.5	89.5	85.5	87.5	83.5	84.5	79.5
	Ensemble Bagged Tree	84.0	77.0	86.2	79.8	89.0	85.0	87.0	83.0	84.0	79.0
	Ensemble Subspace Discriminant	83.5	76.5	86	79.5	88.5	84.5	86.5	82.5	83.5	78.5
	Ensemble Subspace KNN	84.0	77.0	86.5	80.2	89.0	85.0	87.0	83.0	84.0	79.0
Neural Network	Narrow Neural Network	85.0	78.0	86.8	80	90.0	86.0	88.0	84.0	85.0	80.0
	Medium Neural Network	84.5	77.5	87.2	80.5	89.5	85.5	87.5	83.5	84.5	79.5
	Wide Neural Network	84.0	77.0	86	79.5	89.0	85.0	87.0	83.0	84.0	79.0

VI. Conclusion

This paper presented a pilot Electromyography (EMG)-based Digital Twin (DT) framework that integrates signal processing and artificial intelligence for continuous neuromuscular activity monitoring and decision support in healthcare settings. To ensure accurate EMG monitoring within a DT framework, robust model development requires extensive testing and strategic feature data augmentation. Synthetic EMG feature data were generated through Gaussian noise injection, where low-variance noise (mean 0, variance 0.01) improved classification performance by expanding the feature space while preserving physiological signal characteristics. In contrast, a higher noise variance (0.02) introduces feature distortion, ultimately degrading model accuracy.

The integration of Artificial Intelligence (AI), particularly through Machine Learning (ML) and Deep Learning (DL), facilitates automated EMG classification and assists healthcare professionals in making informed decisions. This study investigates five categories of ML and DL algorithms, emphasizing both supervised and semi-supervised classification approaches to enhance diagnostic accuracy and model adaptability. The performance of the proposed EMG DT model was validated using pre-processing metrics such as Signal-to-noise Ratio (SNR), entropy, and peak SNR (pSNR). In addition, AI-based evaluation is conducted using confusion matrices, Receiver Operating Characteristic (ROC) curves, minimum classification error, and Matthews Correlation Coefficient (MCC).

The application of AI using ML and DL provides a foundational step toward automating EMG classification in healthcare settings. This study evaluates five groups of ML and DL algorithms using supervised and semi-supervised learning on Gaussian noise augmented statistical and autonomously extracted feature sets. The experimental results demonstrate that Fine KNN acquired the best supervised performance using statistical feature enlargement with low-variance Gaussian noise augmentation, reaching 94.6% binary and 91.6% multi-class accuracy. Furthermore, semi-supervised autonomous feature extraction using an SAE (32-16-32) architecture yielded superior performance, achieving 96.4% binary and 93.3% multiclass accuracy, highlighting the advantage of compact latent representations for EMG-based activity modeling.

The performance gap between the multiple ML and DL models is affected by feature representation quality, model data compatibility, and robustness to EMG variability. Fine KNN benefits from the locally separable structure of denoised and feature augmented EMG data, while linear and parametric models struggle with non-linear boundaries. In the semi-supervised setting, the SAE (32-16-32) provides a compact and discriminative latent representation, whereas deeper SAEs suffer from reduced generalization due to over-compression and increased complexity. Moreover, low-variance Gaussian augmentation enhances intra-class density and robustness, while higher noise levels distort features and reduce class separability. Overall, the proposed EMG DT demonstrates the feasibility of embedding AI-driven intelligence within a synchronized DT framework for physiologically meaningful activity monitoring. This work establishes a foundational step toward scalable, multi-physiological DT systems for future personalized healthcare applications.

VII. Future Work

The current research is focused towards the development of a pilot design of an EMG DT model for a futuristic Multi-Physiological Digital Twin (MPDT) framework in combination with multiple human vital signs. Although the proposed EMG DT has shown promising outcomes, future development will be focused on assessing the practical usability and scaling toward more human vital signs. The area of focus for future work are:

1) Implement real-world clinical studies integrating respiratory and EMG monitoring to enhance personalized healthcare assessment and validate DT frameworks.
2) Develop standardized data fusion pipelines to integrate heterogeneous signals (respiratory, EMG, ECG, PPG) for a holistic human multi-physiological DT framework.
3) Acquire synchronized multi-sensory patient vital sign data within clinical settings to support the development of data-driven DT models.
4) Implement AI, ML, and DL methodologies to the acquired multi-model data for improved physiological classification and robust DT model realization.
5) Incorporate Explainable AI (XAI) techniques to improve trust, transparency, and clinical adoption of DT-assisted diagnostics and predictions.

VIII. Acknowledgment

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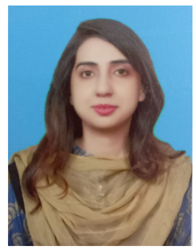
Sagheer Khan is currently working as post doctoral research fellow at SDAIA-KFUPM Joint Research Center for Artificial Intelligence (JRC-AI), Kingdom of Saudi Arabia. He acquired his PhD from Scottish Microelectronic Centre (SMC), School of Engineering, University of Edinburgh, UK. His research interests include Digital Twin (DT), Healthcare 4.0, Sensors, Artificial Intelligence (AI), and Industry 4.0.

Usman Anwar received his B.S. in electrical (telecommunication) engineering from the National University of Computer and Emerging Sciences (NUCES), FAST, Islamabad, Pakistan in 2010 and his M.S. in telecommunication engineering from the University of Engineering and Technology, Taxila, Pakistan in 2016, and Ph.D. degree from The University of Edinburgh with a research focus on neurodegeneration detection through RF and microwave sensors. His research interests include microwave and millimeter-wave antennas, Ultra-wideband MIMO, artificial intelligence, signal processing and flexible biomedical sensors.



Kiran Khurshid received her B.E. in Information and Communication Systems Engineering, and her M.S. and Ph.D. in Wireless Communication and Signal Processing from the National University of Sciences and Technology (NUST), Pakistan. Dr. Khurshid currently serves as an Assistant Professor in the Department of Computer and Software Engineering at the College of Electrical and Mechanical Engineering, NUST. Her research interests include massive MIMO systems, 5G and beyond, IoT, and big data.

Rahmat Ullah is a Lecturer in the School of Computer Science and Electronic Engineering at University of Essex. He previously worked as a Research & Development Associate at University of South Wales. He earned his PhD from University of Edinburgh with research focused on detection of neurodegenerative diseases in collaboration with Centre for the Clinical Brain Sciences. He is an Associate Fellow of the Higher Education Academy, with expertise in software engineering, and signal processing.

Tughrul Arslan (Senior Member, IEEE) holds the Chair of Integrated Electronic Systems with the School of Engineering, University of Edinburgh, Edinburgh, U.K. He is a member of the Integrated Micro and Nano Systems (IMNS) Institute and leads the Embedded Mobile and Wireless Sensor Systems (Ewireless) Group with the University (ewireless.eng.ed.ac.uk). His research interests include developing low power radio frequency sensors for wearable and portable biomedical applications. He is the author of more than 500-refereed papers and inventor of more than 20 patents.

Moataz Ahmed is a faculty member in the Department of Computer Science at King Fahd University of Petroleum and Minerals (KFUPM). His research focuses on artificial intelligence, AI-driven automated software engineering, and applied machine learning, with particular interests in AI security, digital twins, and intelligent systems.