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Electromyographic Signal Analysis for Monitoring and Classifying Hand Muscle Fitness

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ABSTRACT
In fields like sports science, rehabilitation, and ergonomics, hand muscle fitness is a crucial measure of general physical health. One popular non-invasive technique for capturing muscle activity during contraction is electromyography, or EMG. But it is hard to look at raw EMG signals because they have noise and their signals change. To solve this problem, advanced signal processing and machine learning methods are used to find features and group muscle strength. This paper presents a method for classifying hand muscle strength (Low, Medium, High) from Electromyography (EMG) signals using Convolutional Neural Networks (CNNs) and Multi- Layer Perceptron Model (MLP). EMG signals acquired using the Muscle BioAmp Patchy sensor, were transformed into frequency domain using Fast Fourier Transform (FFT). Four key frequency-domain features Mean Frequency, Peak Frequency, Spectral Frequency and Spectral Entropy were extracted. K- means clustering was initially applied to these features to identify potential groupings. Two supervised learning models were trained using the clustered data: a Convolutional Neural Network (CNN) and a Multi-Layer Perceptron (MLP). The clustered data was then used as input to a CNN model. The CNN effectively learned to classify muscle strength, achieving an overall accuracy of 100%. This approach demonstrates the potential of combining FFT-based feature extraction, K-means clustering and CNNs for accurate and automated muscle fitness assessment. The MLP model, while simpler in architecture, also performed well with an accuracy of 88.46%, making it suitable for applications with limited computational resources. This dual-model approach demonstrates the potential of combining FFT-based feature extraction, unsupervised clustering, and deep learning for accurate, efficient, and automated assessment of muscle strength.

KEYWORDS
Electromyography, Fast Fourier Transform (FFT), Feature Extraction, K-means Clustering, Convolutional Neural Networks (CNNs), Multi Laper Perceptron Model (MLP), Machine Learning, Muscle Strength Classification

1. INTRODUCTION

The assessment of hand muscle fitness is very important in many fields like sports science, rehabilitation, healthcare, and ergonomics. To measure muscle activity, we use a technique called Electromyography (EMG). EMG records the electrical signals produced by muscles when they contract. These signals contain important information about the strength and condition of the muscles. However, analyzing EMG signals directly in the time domain can be difficult because the signals are often very complex and noisy. To solve this problem, we use a mathematical method called Fast Fourier Transform (FFT). FFT changes the signals from the time domain to the frequency domain, making it easier to study and understand the muscle activity. After transforming the signals, we extract important features like Mean Frequency, Peak Frequency, Spectral Energy, and Spectral Entropy. These features help us better understand the muscle condition.

To classify muscle fitness levels, we use machine learning techniques such as K-means clustering and Convolutional Neural Networks (CNNs). K-means clustering helps us group the data into different categories based on their similarities, while CNNs are used to train a model that can automatically classify muscle fitness into Low, Medium, or High categories. This method provides a more accurate, faster, and efficient way to assess muscle strength compared to traditional methods. For this study, EMG data was collected from 45 different people to ensure a wide range of muscle strength levels. This large and diverse dataset helps in building a more reliable and generalized model. Overall, this approach can greatly help in areas like sports training, injury recovery, and health monitoring by providing an easy and scientific way to assess hand muscle fitness.

A EMG signals have been widely recognized for their significant utility in understanding muscle function, strength, and fatigue. These electrical signals, generated by muscle contractions, offer valuable insights into muscle activity and provide a direct measure of muscle behavior. Over time, researchers have explored various methods of analyzing EMG signals [1], with a growing emphasis on the frequency domain, as this approach offers a more comprehensive understanding of muscle performance [2]. Specifically, the application of FFT has proven to be highly effective in converting time-domain EMG signals into frequency-domain data [3]. This transformation simplifies the extraction of meaningful features and enables a clearer analysis of muscle behavior, making it easier to identify patterns and characteristics related to muscle function [4].

Several studies have focused on key frequency-domain features, such as Mean Frequency, Peak Frequency, Spectral Energy, and Spectral Entropy, to characterize the muscle's state [5],[6]. These features are particularly useful for detecting subtle changes in muscle strength, fatigue, and overall muscle health over time. This unsupervised learning approach can help uncover hidden patterns in the EMG data, which can be used for further analysis or to inform future research in muscle classification.

In recent years, CNNs have gained considerable attention for EMG signal analysis [7],[8],[9]. CNNs are particularly powerful due to their ability to automatically learn relevant features from raw data, eliminating the need for manual feature selection. Furthermore, CNNs excel at handling the natural variability present in EMG signals collected from different individuals, making them robust for real-world applications. Their ability to learn hierarchical patterns and features from complex data has made CNNs one of the most promising techniques for EMG analysis [10]. Despite the promising results of CNNs in EMG signal analysis, there is still a need for further research that combines CNNs with frequency-domain features and clustering techniques. Such a combination could enhance the classification accuracy of muscle fitness levels, offering more reliable muscle strength assessments. Integrating these advanced techniques could lead to the development of more efficient and faster assessment methods [11], which could be valuable for professionals in sports science, rehabilitation, healthcare, and related fields [12],[13],[14]. Additionally, more research is required to build larger and more diverse datasets to ensure that the models developed are not only accurate but also reliable and applicable to real-world scenarios [15],[16]. This would help in creating robust systems for muscle fitness evaluation, capable of providing real-time and actionable insights for healthcare practitioners and fitness experts [17],[18]. In addition to the CNN model, this study also explored the use of a Multi-Layer Perceptron (MLP) model for muscle strength classification. The MLP model, although simpler in architecture [21],[22] showed competitive performance with a validation accuracy of 88.46%. This demonstrates its potential as a lightweight alternative for real-time or resource-constrained environments, further supporting the robustness and flexibility of the proposed framework for EMG-based muscle fitness assessment.

II. METHODOLOGY

In this study, we utilized the Muscle BioAmp Patchy sensor to record electrical signals from hand muscles. The raw data underwent preprocessing, including cleaning and filtering, to eliminate noise [19],[20]. Fast Fourier Transform (FFT) was then applied to convert the signals from the time domain to the frequency domain, enabling the extraction of key features such shows Muscle BioAmp Patchy sensor.

EMG signals were acquired from hand muscles using the Muscle BioAmp Patchy sensor, a compact and reliable wearable device designed for recording muscle activity. The sensor was placed on hand muscles to record electrical signals generated during muscle contractions. The collected data was stored in CSV format for further preprocessing and analysis.

Figure 1. Muscle BioAmp Patchy Sensor

A. Data Collection

The Muscle BioAmp Patchy sensor is a small, wearable sensor designed for recording muscle activity (Electromyography or EMG). It is a compact, patch-like device that connects directly to gel electrodes, eliminating the need for electrode cables. This makes it easy to integrate into various Human-Computer Interface (HCI) projects. Figure 1.

A. Preprocessing and Feature Extraction

The raw EMG signals collected using the BioAmp Patchy sensor often contain noise due to body movement, environmental factors, and electrical interference. To ensure accurate analysis and classification, these signals were pre-processed using a structured Python-based pipeline. The preprocessing steps applied are described below:

Signal cleaning (removing artifacts and standardizing the format)

Bandpass filtering (200-250 Hz)

The pre-processed EMG signals were then transformed into the frequency domain using FFT. Four frequency-domain features were extracted:

(1) Mean Frequency (MNF):

MNF is the average frequency, which is calculated as the sum of the product of the EMG power spectrum and the frequency divided by the total sum of the spectrum intensity shown in Eq. (1).

$$MNF = \sum_{i=0}^{n} \frac{f_i Pfi)}{P(fi)} \quad (1)$$

as Mean Frequency (MNF), Peak Frequency (PKF), Spectral Energy (SE), and Spectral Entropy (SpEn). Although the labeled data is not used, K-means clustering was employed to group the data into clusters and infer strength levels based on the extracted features. Lastly, a Convolutional Neural Network (CNN) and Multi-Layer Perceptron (MLP) was used to classify muscle strength levels, with the model trained

(2) Peak Frequency (PKF):

Peak Frequency (PKF) represents the frequency component with the highest magnitude or power within the EMG signal's frequency spectrum. It indicates the dominant frequency present in the muscle activity. Shown in Eq. (2)

$$PKF = \text{argmax } P(fi) \quad (2)$$

(3) Spectral Energy (SE):

Spectral Energy (SE) represents the total power of the EMG signal across the entire frequency spectrum. It essentially quantifies the overall activity level of the muscle in the frequency domain. The Spectral Energy is calculated as the sum of the squared magnitudes of the frequency components obtained from the Fast Fourier Transform (FFT). Shown in Eq. (3)

$$SE = \sum nP(fi) \quad (3)$$

(4) Spectral Entropy (SEn):

Spectral Entropy quantifies the irregularity or randomness of the power distribution across the frequency spectrum of the EMG signal. This normalized version, as shown below, provides a value between 0 and 1, making it easier to compare across different signals. A higher value indicates a more uniform (less predictable) power distribution, while a lower value suggests that the power is concentrated in a few dominant frequencies (more predictable). Shown in Eq. (4)

$$SEn = \sum_{i=1}^{n} \frac{f_i Pfi)}{log_2 \frac{P(fi)}{SE}} \quad (4)$$

Where (fi) is the frequency component, (P(fi)) is thepower spectral density, and (n) is the number of frequency bins. K-means clustering

K-means clustering was applied to the extracted features (MNF, PKF, SE, SEn) to group the data into clusters. The algorithm aims to partition the data into k clusters, where each data point belongs to the cluster with the nearest mean (centroid). In this study, k was set to 3, corresponding to the three levels of muscle strength (Low, Medium, High). The K-means algorithm was implemented using Python.

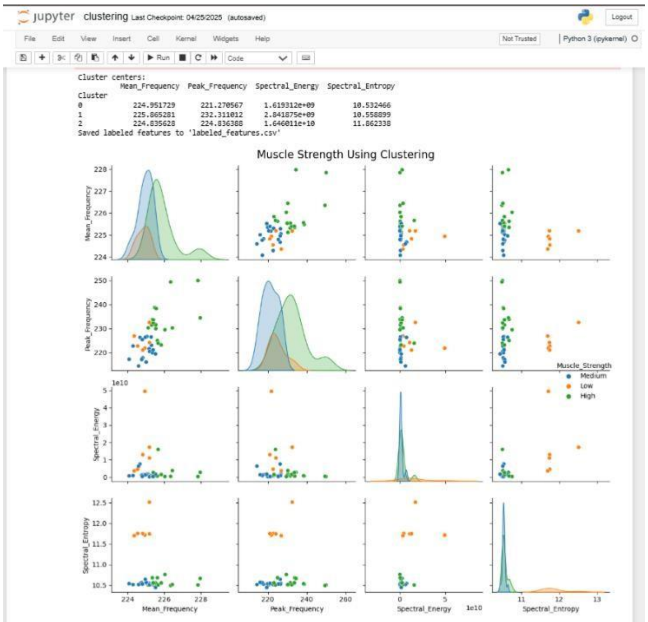


Figure 2. Frequency-Domain Feature Visualization for Clustered Muscle Strength.

III. RESULTS AND DISCUSSIONS

A. Result Of Feature Extraction Using K-Means Clustering Figure 2. illustrates the pairwise relationships and individual distributions of the extracted frequency-domain features – Mean Frequency (Mean Frequency), Peak Frequency (Peak Frequency), Spectral Energy (Spectral Energy), and Spectral Entropy (Spectral Entropy) – for different muscle strength levels as inferred by K-means clustering (Low, Medium, High). The diagonal plots display the kernel density estimates (KDEs) for each feature within each inferred strength level. The off-diagonal plots show scatter plots of each feature pair, with data points coloured according to the inferred strength level. Observations:

-Mean Frequency: The KDE plot suggests a trend towards slightly higher Mean Frequency values for the High inferred strength level compared to the Low and Medium levels. The scatter plots show some separation between the High level and the other two when paired with Peak Frequency and Spectral Entropy.

-Peak Frequency: The distributions of Peak Frequency across the inferred strength levels show considerable overlap in the KDE plot. The scatter plots indicate a wider range of Peak Frequency values for the High inferred strength level.

- Spectral Energy: The KDE plots and scatter plots clearly demonstrate a separation in Spectral Energy across the inferred strength levels. Higher inferred strength levels correspond to substantially higher Spectral Energy values.

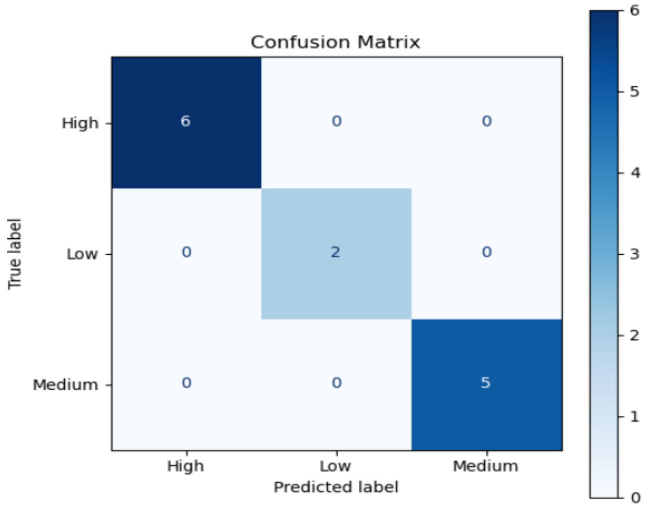
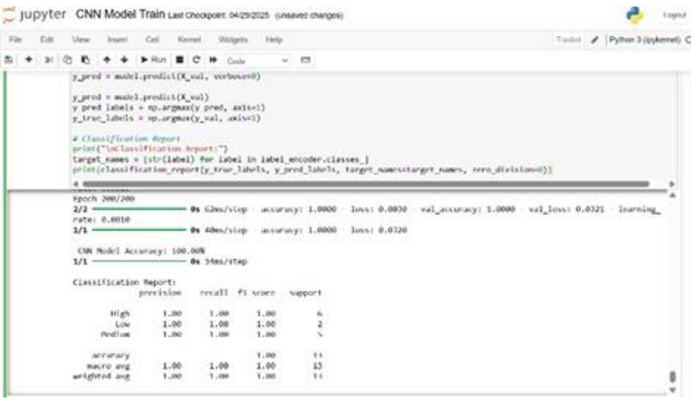


Figure 3. Classification Report of CNN Model

-Spectral Entropy: The KDE plots for Spectral Entropy show a high degree of overlap across all inferred strength levels, suggesting limited discriminatory power of this feature alone



for the clustered groups.

Figure 4. CNN-Based Muscle Strength Classification: Confusion Matrix

B. Result of CNN Model

Figure 3. illustrates classification report of CNN Model. The CNN model demonstrated strong and effective classification of muscle strength levels (High, Low, Medium). It achieved excellent accuracy in identifying 'Low' strength and perfectly predicted the 'Medium' strength while successfully capturing all 'High' strength instances with high precision. The overall 100 % accuracy, supported by favorable average performance metrics, confirms the model's robust and balanced ability to distinguish between different muscle strength levels, even with varying amounts of test data for each.

The CNN model achieved 100% accuracy on the validation set. The detailed classification report further confirms its outstanding performance across all three classes: High, Low, and Medium.

For each class, the model recorded a perfect score of 1.00 for all key evaluation metrics:

• Precision: Indicates that every positive prediction made by the model was correct.

• Recall: Shows that the model successfully identified all actual positive instances of each class.

• F1-Score: The harmonic mean of precision and recall, a perfect score of 1.00 demonstrates the model's excellent balance between these two metrics.

The macro average and weighted average for all metrics are also 1.00, indicating the model's robustness and consistent performance across all classes, even with a slightly imbalanced dataset (as suggested by the 'support' column values of 6, 2, and 5 for High, Low, and medium classes respectively).

C. Confusion Matrix

The confusion matrix (Figure 3) illustrates that the proposed CNN model achieved perfect classification performance across all three muscle strength categories (Low, Medium, and High). Each sample was correctly classified into its respective class, without any misclassifications. This demonstrates the model's strong ability to discriminate between different levels of hand muscle fitness based on extracted frequency-domain EMG features. The results indicate a 100 % classification accuracy on the validation dataset, showcasing the reliability and effectiveness of the developed method.

D. Result of MLP Model

Figure 4. illustrates classification report of MLP Model. Using the extracted frequency-domain EMG features, a MLP model was trained to categorize hand muscle strength into three groups: Low, Medium, and High. The model showed good generalization performance after 200 epochs of training, with training and validation accuracy of 88.46% and 88.46%, respectively. Additionally details regarding how well the model works is found in the classification report. The precision of the model was 1.00 for the High class, 0.89 for the Low class, and 0.78 for the medium class. The balanced detection across all classes was indicated by the recall values of 0.89 (High), 0.89 (Low), and 0.88 (Medium). With a classification accuracy of 88% overall, the corresponding F1-scores were 0.94, 0.89, and 0.82, respectively. Precision, recall, and F1-score all had weighted and macro averages of roughly 0.89, showing the model's dependability and consistency across unequal class distributions.

IV. CHALLENGES

While our method performed well in classifying hand muscle strength, we faced some challenges during the project. These were mostly due to the complex nature of EMG signals, the absence of labeled data, and the need to build a system that works accurately for different individuals. Understanding these challenges is important for improving the approach and helping future research in this area.

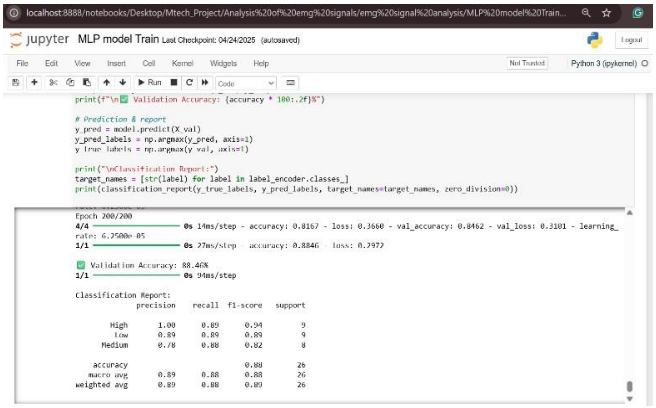


Fig. 5. Classification Report of MLP Model

-Signal Noise and Interference: EMG signals can easily pick up unwanted electrical noise from the environment, body movements, or nearby devices. This makes it harder to detect the actual muscle activity accurately.

-Non-Stationary Nature of EMG: EMG signals vary over time due to muscle fatigue, contraction intensity, and electrode placement, requiring robust preprocessing techniques.

-Individual Variability: Differences in muscle physiology, skin impedance, and electrode positioning between individuals lead to variations in signal characteristics.

-Feature Selection and Optimization: Identifying the most relevant frequency-domain features that effectively

capture muscle strength while avoiding redundant data is a complex task.

-Model Generalization: Ensuring that the trained CNN and MLP model performs well on new, unseen data from different individuals remains a challenge.

-Real-Time Implementation: Developing a system capable of processing EMG signals and classifying muscle strength in real-time requires optimized algorithms and efficient hardware integration.

V. FUTUTRE SCOPE

The current study is the first step toward creating an intelligent, automated system for evaluating muscle fitness, but there are many ways to make it better and add to it. One important area for future research is making a portable, real-time EMG-based monitoring platform that can give feedback right away during daily activities, athletic training, or rehabilitation sessions. This could be done by putting the method into wearable devices, which would let muscle strength be monitored all the time and without any pain outside of a lab. Using multimodal sensor fusion, like combining EMG data with motion capture systems, inertial measurement units (IMUs), force plates, or physiological sensors (like heart rate monitors), could give a complete picture of how well the neuromuscular system is working. This kind of integration would let the system look at both muscle activity and movement patterns and mechanical output, leading to richer insights for sports science, physiotherapy, and ergonomics.

Additionally, expanding the dataset to include a larger and more diverse participant pool, covering different age groups, genders, body compositions, and health conditions, would help to improve the robustness and generalizability of the proposed model. Advanced deep learning techniques, including hybrid architectures that combine CNNs with recurrent networks like LSTMs or Transformers, could be explored to better capture temporal dependencies and subtle variations in EMG signals. Furthermore, optimization of computational efficiency and energy consumption will be essential for deploying the system on edge devices or embedded platforms, enabling use in wearable technology.

From a clinical perspective, the methodology could be adapted for the diagnosis and progression monitoring of neuromuscular disorders such as muscular dystrophy, ALS, or peripheral neuropathy. In rehabilitation, it could facilitate patient-specific recovery tracking and provide therapists with objective metrics to adjust treatment plans in real time. In the domain of sports science, the system could assist coaches and athletes in designing personalized training programs by detecting muscle fatigue early and preventing overuse injuries. Ultimately, by combining real-time processing, multimodal data integration, and personalized analytics, the proposed system could evolve into a powerful tool that bridges healthcare, sports, and human–computer interaction, making muscle fitness monitoring accessible, efficient, and highly accurate across a wide range of applications.

VI. CONCLUSION

This paper has demonstrated the effectiveness of combining advanced signal processing with deep learning for automated hand muscle strength classification. By using the BioAmp Patchy sensor, EMG signals were collected and transformed into the frequency domain through Fast Fourier Transform (FFT), enabling the extraction of key frequency- domain features such as Mean Frequency, Peak Frequency, Spectral Energy, and Spectral Entropy. In the absence of labeled data, K-means clustering was employed to identify natural groupings corresponding to low, medium, and high strength levels. These cluster assignments were then used to train a Convolutional Neural Network (CNN), which achieved an impressive 100 % classification accuracy. This hybrid approach, integrating unsupervised and supervised learning, showcases the potential of leveraging machine learning to create more objective, consistent, and efficient muscle fitness evaluation systems compared to traditional manual assessments. The findings of this study show how well deep learning models classify hand muscle fitness based on electromyographic (EMG) signals. A comparison between a convolutional neural network (CNN) and a multilayer perceptron (MLP) was carried out.

According to our research, the CNN architecture is remarkably well-suited to this time-series classification task. On the validation dataset, the CNN model obtained a perfect 100% accuracy, precision, recall, and f1-score. The CNN's capacity to automatically extract and learn intricate, hierarchical features from the raw EMG signals—features that are essential for precise classification—is responsible for this exceptional performance.

The accuracy of the MLP model was 88.46%, indicating that its fully connected layers were less successful in identifying the complex patterns in the EMG data. This is a notable improvement over the MLP model.

In conclusion, the CNN model that was created offers a reliable and extremely accurate way to automatically track and categorize hand muscle fitness. The CNN's remarkable performance demonstrates its potential for practical uses in fields like sports science, rehabilitation, and clinical diagnostics where accurate and trustworthy muscle health classification is crucial.

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DISCLOSURE OF INTERESTS

The authors have no conflicts of interest to declare.

AUTHORS CONTRIBUTION STATEMENT

Gayatri Phadatare contributed to the conceptualization, methodology design, software development for EMG signal processing and CNN model and MLP model, data acquisition and preprocessing, result analysis, and drafting of the original manuscript. Anagha Deshpande provided conceptual guidance, supervised the research, contributed to methodology and analysis refinement, provided necessary resources, validated the findings, and was responsible for reviewing and editing the manuscript.

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