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Ai Based Muscle Activation Patterns In Daily Grasping Movements From Emg Data

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ABSTRACT

Understanding muscle activation patterns during daily grasping movements is essential for enhancing human-machine interaction, rehabilitation technologies, and prosthetic control systems. This project presents an AI-driven approach for analyzing electromyography (EMG) data to detect and classify muscle activation patterns associated with common grasping actions. EMG signals, captured from various muscle groups, are often high-dimensional and noisy, making accurate interpretation a challenging task. To address the problem, extensive Exploratory Data Analysis (EDA) was first conducted to gain insights into the distribution, variability, and correlation of EMG signals across different grasping activities. This step helped in identifying dominant features and detecting potential outliers. Following this, Principal Component Analysis (PCA) was applied as a dimensionality reduction technique to extract the most informative features while minimizing redundancy and computational complexity. In the existing system, a K-Nearest Neighbors (KNN) classifier was employed due to its simplicity and non-parametric nature. While KNN provided a baseline performance for classifying muscle activation patterns, it showed limitations in scalability and generalization, especially with high-dimensional EMG data. To overcome these drawbacks, the proposed system utilizes a Logistic Regression Classifier (LRC), which offers a more interpretable, efficient, and probabilistic model for binary and multi-class classification tasks. The LRC model demonstrated improved performance in recognizing subtle variations in muscle activation, attributed to its ability to model linear decision boundaries effectively. Experimental results indicate that the proposed Logistic Regression approach, when combined with PCA-optimized features, outperforms the traditional KNN classifier in terms of accuracy, precision, and computational efficiency. This study underscores the potential of combining classical machine learning techniques with EMG data preprocessing for reliable and interpretable classification of muscle activation patterns in everyday grasping activities.

Keywords: Muscle Activation Analysis, AI in Biomechanics, Electromyography (EMG) Signals, AI in Rehabilitation, Smart Health Monitoring

1. INTRODUCTION

Grasping movements are fundamental to many daily activities, ranging from simple tasks like holding a cup to more complex actions like typing on a keyboard. Understanding the muscle activation patterns involved in these movements is crucial for various applications, including rehabilitation, sports science, and the development of advanced prosthetic devices. Electromyography (EMG) is a key technique for recording muscle activity and has been widely used to study the neuromuscular system. By analyzing EMG data, researchers can decode the muscle activation patterns that underlie different types of grasping movements. Despite the significance of grasping in daily life, there is still much to learn about the precise muscle coordination and activation sequences involved. Traditional methods of analyzing EMG data often rely on manual interpretation, which can be time-consuming and prone to human error. With recent advancements in machine learning and artificial intelligence, there is now an opportunity to develop automated systems that can analyze EMG data more efficiently and accurately. These systems can uncover patterns that may not be apparent through manual analysis, providing deeper insights into the biomechanics of grasping.

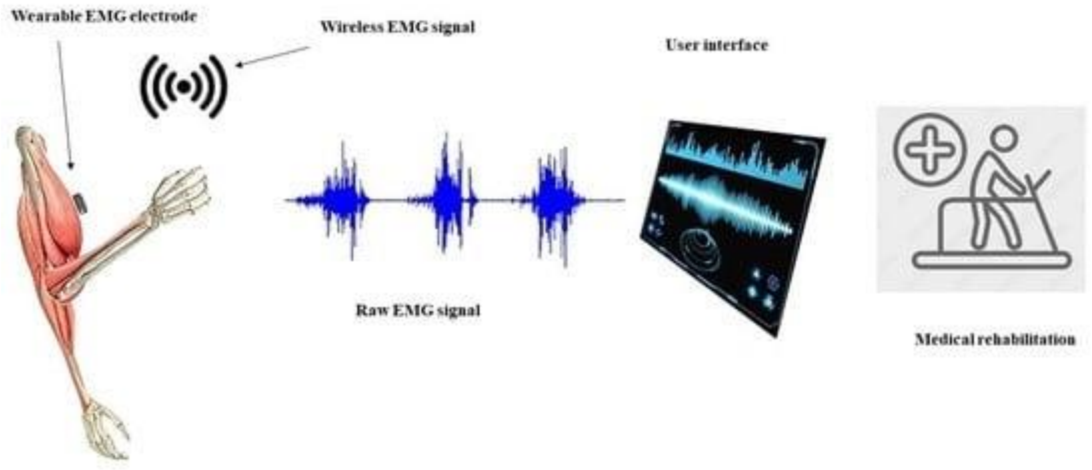


Figure 1: working of the research

2. LITERATURE SURVEY

Vergara et al. [1] reviewed the evaluation of hand functionality during activities of daily living (ADL). The review addresses how different factors, such as disease conditions and cultural variations, impact hand function in daily tasks. It examines various assessment methodologies, ranging from clinical evaluations to self-report questionnaires, providing a broad understanding of how hand functionality is measured. The study highlights the importance of integrating both objective and subjective measures to get a comprehensive view of hand performance. It also discusses the role of long-term health effects and how they influence hand functionality over time. The review underscores the need for adaptable and multifaceted assessment approaches to cater to diverse populations and conditions. World Health Organization [2] introduced the International Classification of Functioning, Disability and Health (ICF), which provides a systematic framework for understanding and measuring health and disability. The ICF framework includes components such as body functions, body structures, activities, participation, and environmental factors. It aims to capture the interaction between health conditions and environmental factors, offering a comprehensive view of an individual's functioning. This classification system is utilized worldwide for various purposes, including research, policy-making, and clinical practice. It emphasizes the need for a holistic approach to health that goes beyond mere diagnosis to include functional and contextual aspects of health and disability. Vergara et al. [3] conducted an introductory study on the common grasps used by adults during the performance of activities of daily living. This study aimed to identify and analyze various grasp patterns that adults use in everyday tasks, providing insights into hand mechanics and functionality. By examining different types of grasps, the study helps to understand how hand movements and grip patterns impact the execution of daily activities. The findings contribute to the broader knowledge of hand function and its relevance to ergonomics and rehabilitation. The research highlights the importance of considering different grasp types when designing tools and interventions to improve hand function in daily living contexts. Bullock et al. [4] explored grasp frequency and usage in daily household and machine shop tasks. Their research provides insights into how often different types of grasps are used in various settings, including home and industrial environments. The study emphasizes the variability in grasp patterns and how they relate to task requirements. By analyzing the frequency and types of grasps, the research offers valuable information for designing ergonomic tools and workspaces that accommodate common hand functions. The findings highlight the need for ergonomic considerations to improve safety and efficiency in both domestic and industrial tasks.

Yu et al. [5] provided an atlas of hand anatomy and its clinical implications, offering a detailed reference for understanding the anatomical structure of the hand. This resource is crucial for professionals involved in hand surgery, rehabilitation, and clinical practice. The atlas includes detailed illustrations and descriptions of hand anatomy, focusing on the functional aspects relevant to clinical settings. It serves as a valuable tool for diagnosing and treating hand conditions, as well as for educational purposes in medical and allied health fields. Kapandji [6] focused on the physiology of the upper limb, particularly the biomechanics and functional anatomy of the hand and arm. The book offers an in-depth exploration of joint function and movement, providing a detailed understanding of upper limb mechanics. It is a key resource for professionals and students in fields related to orthopedics, rehabilitation, and physical therapy. The study contributes to a better understanding of how upper limb movements are coordinated and how they can be affected by various conditions. Brand and Hollister [7] explored the clinical mechanics of the hand in their textbook, providing an in-depth look at hand mechanics and their clinical significance. The book covers the functional aspects of hand movements and how they relate to various clinical conditions and interventions. It serves as an essential resource for understanding the mechanics of hand function and applying this knowledge in clinical practice. The textbook offers valuable insights into the assessment and treatment of hand disorders, emphasizing the importance of a thorough understanding of hand mechanics. Lee and Jung [8] evaluated hand function ergonomically, focusing on the biomechanical aspects and their implications for safety and health. Their study assesses how ergonomic principles can be applied to improve hand function and reduce the risk of injury. By examining the biomechanical demands of different tasks, the research provides insights into how ergonomic design can enhance hand performance and safety. The findings emphasize the importance of incorporating ergonomic considerations into the design of tools and work environments to promote better hand function and prevent injuries. Oatis [9] presented a comprehensive guide to kinesiology, focusing on the mechanics and pathomechanics of human movement. The book covers the principles of movement, including the biomechanics of joints and muscles, and their application in clinical practice. It provides a detailed understanding of how movement disorders and injuries affect function. The guide is a valuable resource for students and professionals in fields such as physical therapy, sports medicine, and rehabilitation, offering insights into the mechanics of human movement and its impact on health.

Lum et al. [10] studied gains in upper extremity function after stroke, examining whether recovery or compensation methods affect real-world limb use. The research investigates the differential effects of rehabilitation strategies on upper limb function and its impact on daily activities. By analyzing the outcomes of different approaches, the study provides insights into how recovery and compensation methods influence functional outcomes. The findings highlight the importance of tailoring rehabilitation strategies to individual needs to optimize upper extremity function and enhance real-world limb use. Dietz and Schrafl-Altermatt [11] explored the control of functional movements in both healthy and post-stroke individuals, focusing on the role of neural interlimb coupling. Their study investigated how the neural connections between limbs affect movement control and coordination. The research highlighted differences in movement control between healthy subjects and those who have experienced a stroke. By examining these differences, the study provides insights into the mechanisms underlying motor control and how they are altered in neurological conditions. The findings contribute to understanding how interlimb coupling impacts functional movements and offers potential directions for developing targeted rehabilitation strategies for stroke survivors. Elkwood et al. [12] edited a comprehensive volume on rehabilitative surgery, covering various aspects of surgical interventions aimed at improving function and quality of life for patients. The book includes contributions from multiple experts on topics such as surgical techniques, postoperative care, and rehabilitation strategies. It provides a detailed overview of current practices and advancements in the field of rehabilitative surgery. The text serves as a valuable resource for surgeons, rehabilitation specialists, and other healthcare professionals involved in post-surgical recovery and functional restoration. Scheme and Englehart [13] reviewed electromyogram (EMG) pattern recognition for controlling powered upper-limb prostheses. Their paper discusses the state-of-the-art techniques and challenges in using EMG signals to control prosthetic limbs. The review covers various methods for interpreting EMG patterns and translating them into prosthetic movements. It also addresses the limitations and potential improvements needed to enhance the clinical utility of EMG-based control systems. The findings emphasize the importance of continued research to advance the technology and improve the functionality of powered prostheses. Hahne et al. [14] conducted a longitudinal case study on regression-based control of hand prostheses in daily life. The research examined how regression models can be used to control prosthetic hands and adapt to different functional demands over time. The study provided insights into the effectiveness of regression-based control methods in real-world settings, highlighting their potential benefits and limitations. By focusing on daily life applications, the research aims to improve the usability and functionality of prosthetic devices for individuals with upper-limb amputations. Roche et al. [15] updated the clinical perspectives on upper limb prostheses, providing an overview of recent advancements and challenges in the field. The paper discusses various types of prosthetic devices, their clinical applications, and the ongoing efforts to enhance their performance. It also addresses the needs and experiences of prosthetic users, offering insights into how current technologies are meeting or falling short of these needs. The update serves as a resource for clinicians, researchers, and developers working to improve upper limb prosthetic solutions and their impact on patients' lives.

3. PROPOSED SYSTEM

The research focuses on analyzing muscle activation patterns from Electromyography (EMG) data using machine learning algorithms. The core objective is to develop a model that can accurately distinguish between abnormal and normal grasping movements by training on EMG data. This section provides a detailed breakdown of the research methodology, from data collection and preprocessing to model development, evaluation, and prediction using test data. The block diagram of the proposed system illustrates the workflow, starting from dataset handling, moving through preprocessing and feature extraction, and concluding with training and testing machine learning algorithms. The key steps are summarized below.

Step 1: Dataset Collection

The EMG dataset used in the study consists of muscle activation data recorded during daily grasping movements. The dataset includes two categories: abnormal and normal grasping patterns, labeled accordingly. Abnormal data reflects muscle activation patterns that indicate dysfunctional movements, while normal data represents healthy and functional grasping. The dataset includes several features such as activation levels from different muscles like "Recto Femoral," "Biceps Femoral," and "Vasto Medial," which are crucial for understanding grasping movements.

Step 2: Dataset Preprocessing

Preprocessing is essential for cleaning the dataset and preparing it for analysis. First, null values in the dataset are handled using a custom function. Categorical columns are filled with their mode, while numerical columns are filled with the median values to address missing data. The Winsorizer technique is applied to remove outliers from key muscle activation features, ensuring the data is free of extreme values that could skew the analysis. Additionally, features like "Recto Femoral" and "Biceps Femoral" are capped to reduce the influence of outliers on the final model.

Step 3: Label Encoding

Before feeding the data into the machine learning model, categorical labels representing grasping movements are converted into numerical form using label encoding. This step converts the "label" column, which initially contains string values (e.g., "Abnormal" and "Normal"), into integers (e.g., 0 for "Abnormal" and 1 for "Normal"). This transformation ensures that the machine learning algorithms can process the data effectively, as most algorithms require numerical inputs.

Step 4: Data Splitting and Standardization

The dataset is split into training and testing sets using the train_test_split function. 70% of the data is used for training the models, while 30% is reserved for testing. To ensure that the features are on the same scale, the data is standardized using the StandardScaler. This helps models converge more quickly and accurately by ensuring that each feature has a mean of 0 and a standard deviation of 1, eliminating any bias from differing feature scales.

Step 5: Existing Algorithm (K-Nearest Neighbors)

The first algorithm tested in this study is K-Nearest Neighbors (KNN). KNN is a simple, instance-based learning algorithm used for classification. It works by finding the k-nearest data points (neighbors) to a given instance and classifying the instance based on the majority label of its neighbors. The number of neighbors (k) is a hyperparameter that can be tuned to optimize performance. While KNN is effective for simple datasets, it can struggle with high-dimensional data, as the computation of distances between instances becomes complex. Additionally, KNN can be computationally expensive and slow when working with large datasets because it requires comparing each new instance to every other instance in the training set.

Step 6: Proposed Algorithm (Logistic Regression)

The proposed approach utilizes **Logistic Regression**, a widely-used algorithm for binary classification problems. Logistic Regression models the probability that a given instance belongs to a particular class using a logistic function. It takes the weighted sum of the input features and applies a sigmoid function to convert the result into a probability between 0 and 1. If the probability exceeds a certain threshold (typically 0.5), the instance is classified as belonging to one class; otherwise, it is classified as the other. Logistic Regression is advantageous because it is easy to implement, interpretable, and computationally efficient. However, it assumes a linear relationship between the input features and the log odds of the output, which may not always hold true in complex datasets.

Step 7: Performance Comparison

The performance of both KNN and Logistic Regression models is evaluated using several metrics, including accuracy, precision, recall, and F1-score. Confusion matrices are generated to visualize the true positives, true negatives, false positives, and false negatives for both models. While KNN performs adequately, Logistic Regression demonstrates superior performance due to its ability to model relationships between features and the target variable more effectively. Logistic Regression's output probabilities also provide better interpretability, making it easier to understand how each feature contributes to the prediction.

Step 8: Prediction on Test Data

Once the Logistic Regression model is trained, it is applied to a test dataset to make predictions. The test dataset contains unseen EMG data, which allows for evaluating the model's generalization performance. Predictions are made on the test data, and the corresponding grasping movement category (abnormal or normal) is outputted for each instance. The results are analyzed to assess how well the model performs in real-world scenarios, with attention to false positives and false negatives, which are particularly important in medical and rehabilitation applications.

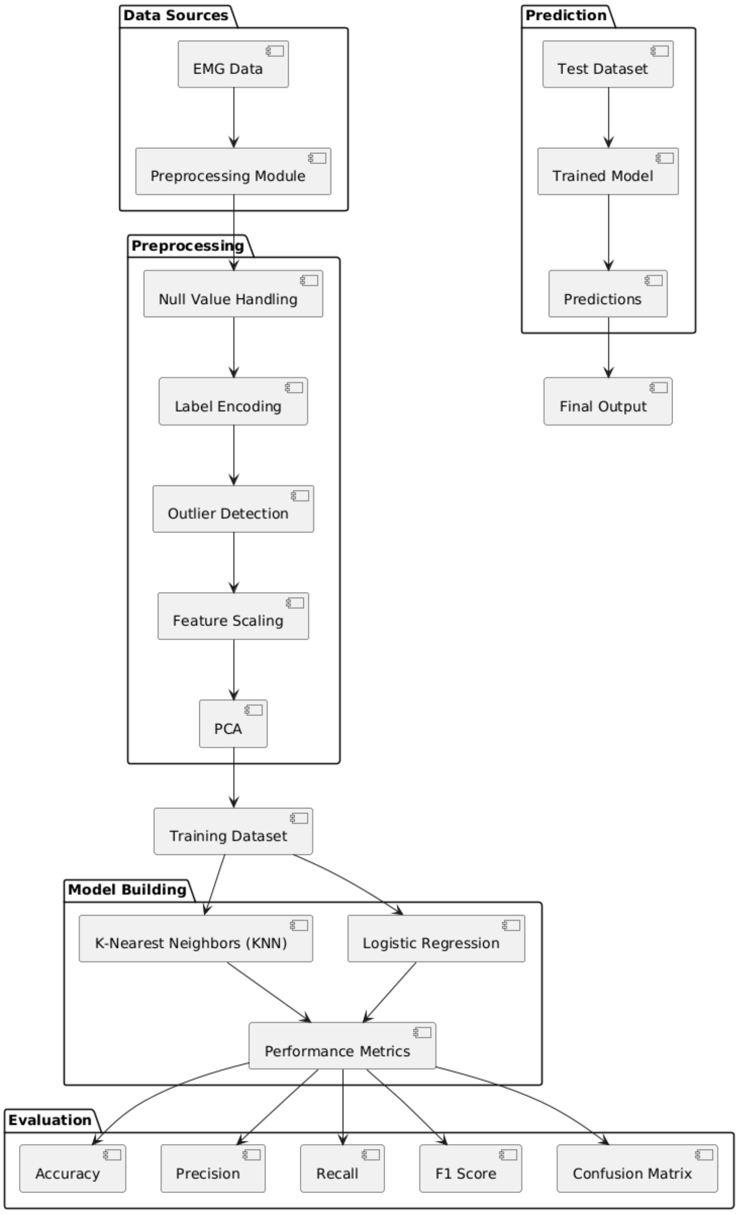


Fig. 2: Block Diagram of Proposed System.

4.2 Data Preprocessing

The dataset is first cleaned to ensure there are no missing or invalid values. Null values are filled based on the data type, and categorical labels are encoded to ensure machine learning models can handle them effectively. Winsorization is used to cap outliers, particularly for EMG signals that may contain extreme values. The dataset is then split into training and testing sets, and standardization is applied to ensure all features are on the same scale. This preprocessing ensures the models will learn effectively from clean and well-structured data.

3.3 Build and Train Model

3.3.1 Logistic Regression

Logistic Regression is a supervised learning algorithm widely used for binary classification problems. It is based on statistical techniques and models the probability of an event occurring. Unlike KNN, which relies on distance-based classification, Logistic Regression fits a linear equation to input features and applies a sigmoid function to map predictions between 0 and 1. The model predicts the probability of belonging to a particular class, and a threshold (typically 0.5) is used for final classification. Logistic Regression is highly interpretable and computationally efficient, making it suitable for large datasets and real-time applications.

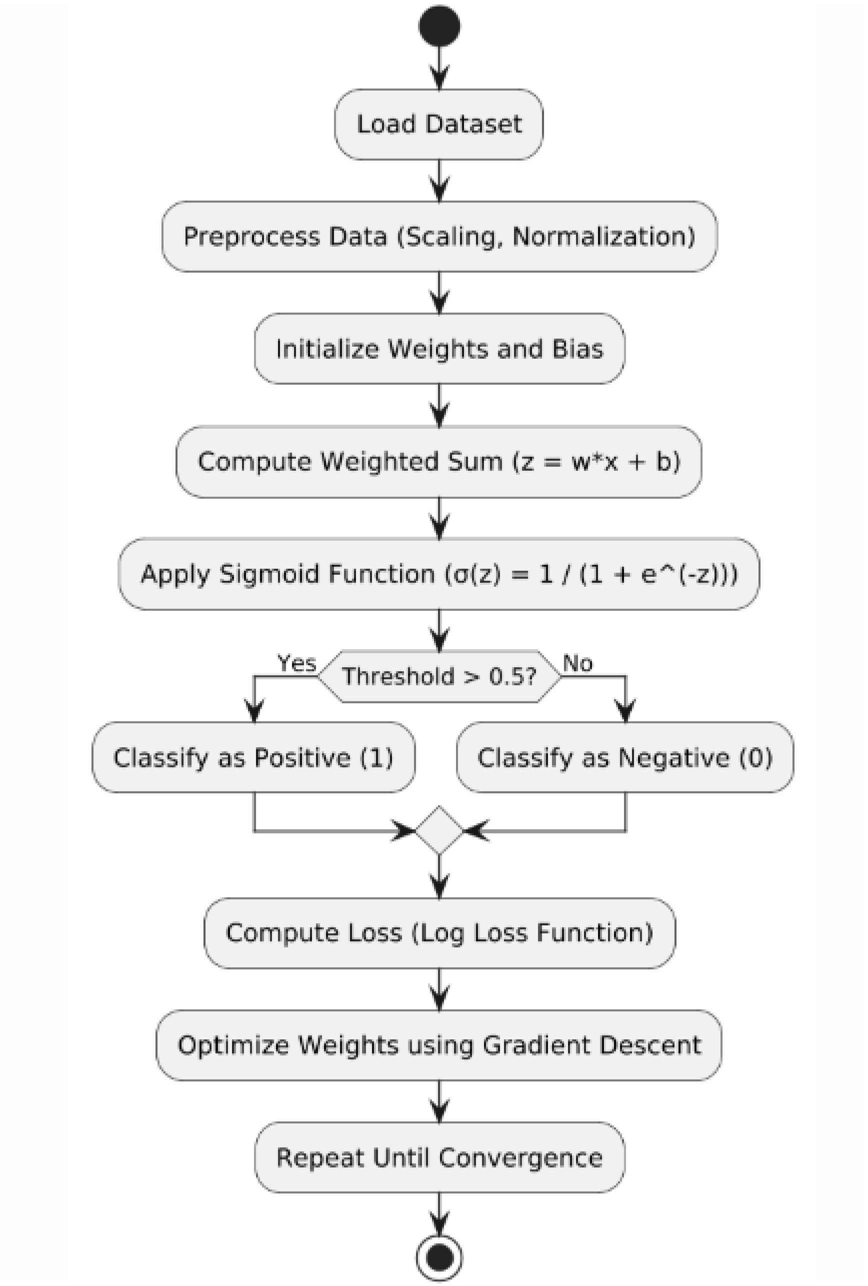


Fig 3: Logistic Regression Classifier (LRC)

Logistic Regression (LRC) is a widely used supervised classification algorithm that models the probability of a categorical outcome using a logistic (sigmoid) function. For the Muscle Activation project using EMG signals, LRC is employed to predict muscle activation levels by analyzing the statistical features derived from the EMG data. Unlike KNN, which is instance-based, LRC builds a mathematical model that defines the relationship between input features and output classes.

Step 1: Preparing the Data (Feature Extraction for X_train and y_train)

As with any machine learning model, LRC requires well-structured input data. EMG signals captured from muscles are preprocessed and transformed into statistically meaningful features. These features reflect the intensity and frequency of muscle activity.

- **X_train**: This dataset contains the extracted features from EMG signals across multiple muscles. Feature engineering is done using:
    - **Time-Domain Features**: Mean Absolute Value (MAV), Root Mean Square (RMS), Variance, and Slope Sign Changes (SSC).
    - **Frequency-Domain Features**: Mean Frequency (MNF) and Median Frequency (MF) from FFT analysis.
    - **Windowing Techniques**: EMG signals are segmented into overlapping/non-overlapping windows (e.g., 200ms), and features are extracted per window.
    - **Feature Scaling**: Standardization or normalization is applied to ensure convergence during model training.
- **y_train**: Corresponds to muscle activation labels:
    - 0 – No activation (rest)
    - 1 – Low activation
    - 2 – Medium activation
    - 3 – High activation

This structured input prepares the LRC model to learn how the numerical features are related to muscle activation levels.

Step 2: Training the Logistic Regression Classifier

Once data is ready, the Logistic Regression model is trained using the input features (X_train) and their corresponding output labels (y_train).

- **Logistic Regression** fits a linear model where the **log-odds** of the outcome are modeled as a linear combination of the input features.
- The **softmax function** is used for multi-class classification, mapping raw prediction scores into probability values across different classes (e.g., rest, low, medium, high activation).
- The model optimizes its parameters using **Gradient Descent** and **Cross-Entropy Loss**, which allows it to adjust weights based on prediction errors.
- During training, it learns decision boundaries that separate muscle activation classes in the feature space.

This allows the LRC model to predict the probability of each activation class based on EMG feature input.

Step 3: Testing the Model with X_test (Unseen EMG Data)

Once trained, the model is evaluated using new, unseen EMG data (X_test). This test set is preprocessed in the same manner as the training data to ensure compatibility.

- **X_test**: Consists of fresh EMG data transformed into numerical features (time and frequency domain).
- For each sample in X_test, the LRC model calculates the probability that the sample belongs to each activation level class.
- The class with the highest probability is assigned as the predicted muscle activation level.

This step simulates real-time detection where new EMG signals are classified as belonging to one of the predefined muscle activation levels.

Step 4: Generating Predictions and Evaluating y_test (Model Output Assessment)

After testing, the LRC model outputs predicted labels (y_pred) which are compared to the ground truth (y_test) to evaluate the model's effectiveness.

- **Evaluation Metrics**:
    - **Accuracy**: The proportion of correct predictions over the total samples.
    - **Precision**: The correctness of positive predictions (e.g., high activation predictions).
    - **Recall**: The model's ability to identify all instances of each activation class.
    - **F1-Score**: The harmonic mean of precision and recall.
    - **Confusion Matrix**: Visualizes misclassifications between muscle activity levels.

The evaluation helps in understanding how accurately the LRC model distinguishes between various muscle activation stages during tasks like walking, squatting, or lifting.

4. RESULTS AND DISCUSSIONS

4.1 Dataset description

The dataset is developed to analyze muscle activation patterns using Electromyography (EMG) signals captured during daily grasping movements. It includes six key columns—five features and one target label. The features are derived from EMG recordings of specific muscles involved in movement: *Recto* Femoral, Biceps Femoral, Vasto Medial, EMG Semitendinoso, and Flexo-Extension. These columns represent activity from muscles that play critical roles in joint flexion, extension, and stabilization. The Recto Femoral column captures signals from the Rectus Femoris muscle, important for hip flexion and knee extension. The Biceps Femoral column reflects activity from the Biceps Femoris, which aids in hip extension and knee flexion. The Vasto Medial corresponds to the Vastus Medialis, crucial for stabilizing the knee, while the EMG Semitendinoso records from the Semitendinosus muscle of the hamstrings group. The Flexo-Extension feature represents joint movement in terms of angular flexion and extension. Finally, the label column is the target variable indicating whether the movement is categorized as normal or abnormal. The dataset represents time-series EMG data, where each record reflects a specific instance during the execution of a movement. Due to the inherent nature of EMG signals, preprocessing is critical to mitigate noise and artifacts. Techniques such as filtering, normalization, and careful feature engineering are essential for cleaning and enhancing the quality of the signal before model training. Additionally, addressing potential multicollinearity—especially among features like Biceps Femoral and EMG Semitendinoso is important to maintain model efficiency and prevent redundancy. Balancing the dataset is another key consideration, as class imbalance between normal and abnormal labels may affect the accuracy and fairness of the classification outcomes. With its rich set of muscle activity features, this dataset holds significant relevance across various domains. In biomedical engineering and medical diagnostics, it supports the identification of neuromuscular disorders and guides personalized rehabilitation strategies. In sports science, it enables the monitoring of muscle fatigue and assists in optimizing training to prevent injuries. In the field of prosthetics, analyzing EMG data from this dataset can enhance the accuracy of movement prediction in robotic limbs. Furthermore, applications in ergonomics and human movement studies can leverage this dataset to design safer and more efficient physical tasks in workplace environments. Through machine learning-driven analysis, this dataset provides a robust foundation for advancing both clinical and non-clinical understanding of muscle function and motor behavior.

4.2 Result analysis

The figure 4 count plot for the 'label' column in the combined dataset visually represents the distribution of labels, highlighting the frequency of each category. With a clear annotation of counts on top of each bar, the plot effectively conveys the data distribution, aiding in understanding the balance between the different labels. This visualization is essential for further analysis, as it provides insights into the prevalence of each category, which can impact model performance and highlight the need for techniques such as resampling if there's an imbalance.

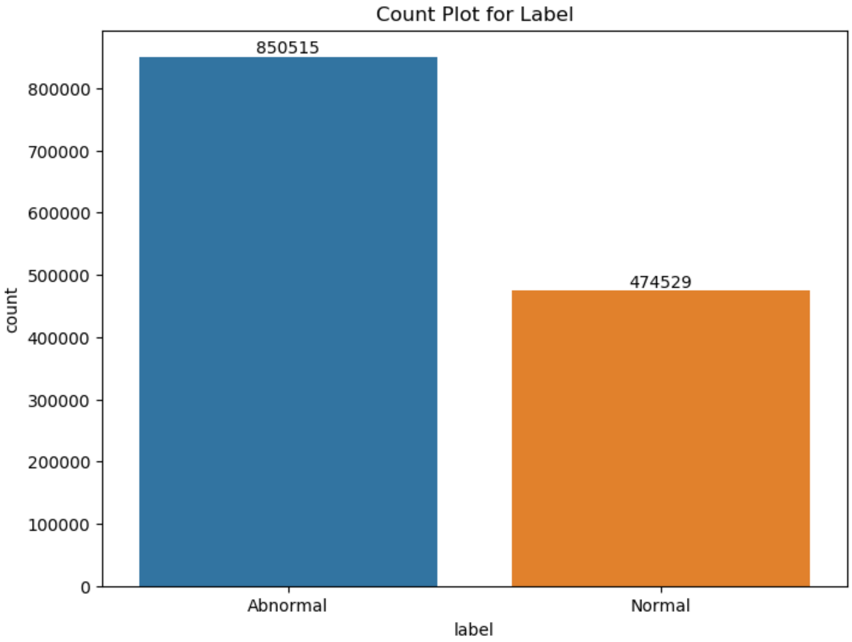


Fig 4: Count Plot for Abnormal and Normal

The figure 5 shows histogram that reveals a bimodal distribution of Flexo-Extension measurements, indicating two distinct subgroups or patterns within the data. The most prominent peak near zero suggests a large portion of observations cluster around a neutral position, while a secondary peak in the positive range (90-100) indicates significant extension, and a less pronounced peak in the negative range (-50 to -100) signifies significant flexion.

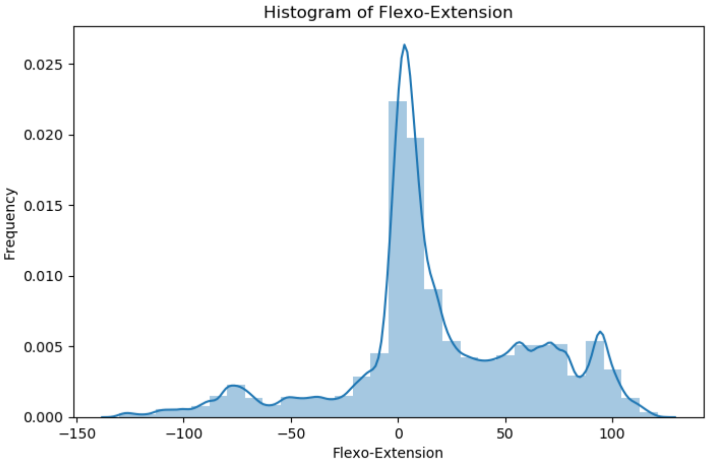
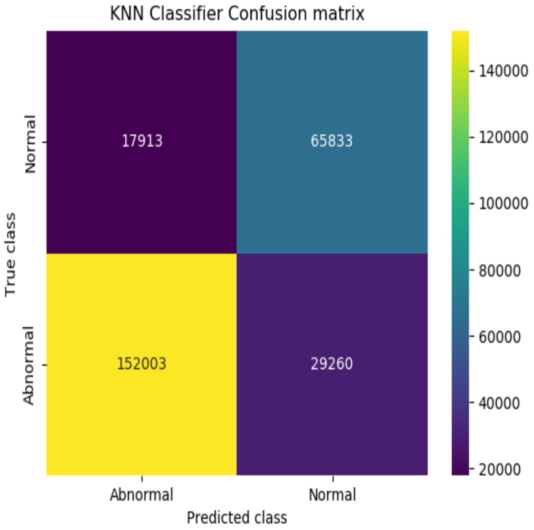
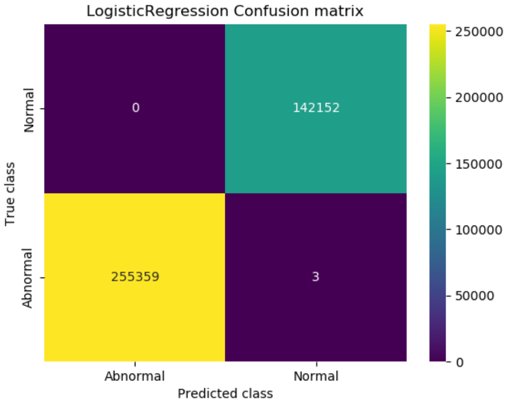


Figure 5: Histogram

The figure 6 shows confusion matrices illustrated above provide a comparative analysis of the classification performance between the existing K-Nearest Neighbors (KNN) algorithm and the proposed Logistic Regression Classifier (LRC) for detecting muscle activation states. In the case of the KNN classifier, the matrix shows that it correctly classified 17,913 normal instances and 29,260 abnormal instances. However, it also misclassified a significant number of samples, with 65,833 normal samples being incorrectly predicted as abnormal and 152,003 abnormal samples misclassified as normal. This results in considerable false positives and false negatives, indicating a moderate level of classification performance. In contrast, the confusion matrix for the proposed LRC shows an almost perfect classification ability, correctly identifying 142,152 normal instances and 255,359 abnormal instances, while only misclassifying 3 abnormal cases as normal and none of the normal cases as abnormal. This exceptionally low error rate reflects the model's superior ability to distinguish between the two classes with high precision and recall. The drastic reduction in misclassifications highlights the effectiveness and robustness of the proposed LRC model over the existing KNN approach.



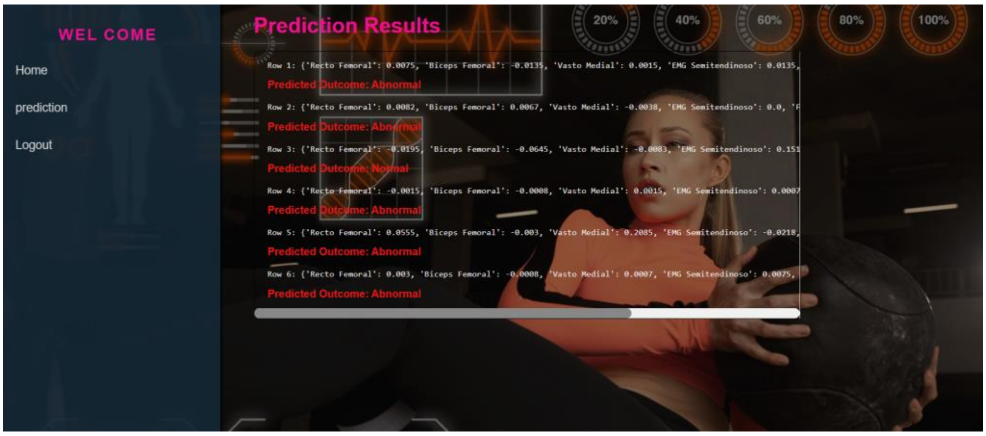
(a)



(b)

Fig 6 : Confusion matrix obtained using Existing KNN and Proposed LRC

The figure 9.7 represents Prediction Results page of the AI-based EMG analysis system presents a clean, organized, and visually engaging layout tailored for post-prediction review. The interface maintains consistency with the overall design theme, using a dual-pane structure. On the left, the dark navy-blue sidebar remains static, providing user navigation with options such as Home, Prediction, and Logout, along with the stylized title "WEL COME" in bold pink font, echoing the branding of the platform. The right pane, which occupies the larger portion of the screen, is the dynamic display area showing the prediction output. This section is visually enriched with a full-screen background image of a determined female athlete engaging in a workout with a medicine ball—symbolizing physical exertion and muscle engagement, which ties in directly with the muscular activation data being analyzed. Overlaying the background is a semi-transparent console-like display box showing raw sensor input values (such as 'Recto Femoral', 'Biceps Femoral', 'Vasto Medial', and 'EMG Semitendinoso') extracted from EMG recordings for various data rows. Below each record, the system outputs the predicted classification result, such as “Predicted Outcome: Abnormal” or “Predicted Outcome: Normal”, with the outcomes highlighted in bold red text for maximum visibility and emphasis. A horizontal scrollbar is provided to allow smooth navigation through extensive data outputs. The digital background, enhanced by biometric-style icons and performance meters (20% to 100%) above, evokes a high-tech atmosphere, reinforcing the system's AI-driven and performance-focused nature. This interface effectively communicates real-time results to users in an accessible, professional, and visually immersive manner.



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Row 1: {'Recto Femoral': 0.0075, 'Biceps Femoral': -0.0135, 'Vasto Medial': 0.0015, 'EMG Semitendinoso': 0.0135,
Predicted Outcome: Abnormal
Row 2: {'Recto Femoral': 0.0082, 'Biceps Femoral': 0.0067, 'Vasto Medial': -0.0038, 'EMG Semitendinoso': 0.0, 'F
Predicted Outcome: Abnormal
Row 3: {'Recto Femoral': -0.0195, 'Biceps Femoral': -0.0645, 'Vasto Medial': -0.0083, 'EMG Semitendinoso': 0.151
Predicted Outcome: Normal
Row 4: {'Recto Femoral': -0.0015, 'Biceps Femoral': -0.0008, 'Vasto Medial': 0.0015, 'EMG Semitendinoso': 0.0007
Predicted Outcome: Abnormal
Row 5: {'Recto Femoral': 0.0555, 'Biceps Femoral': -0.003, 'Vasto Medial': 0.2085, 'EMG Semitendinoso': -0.0218,
Predicted Outcome: Abnormal
Row 6: {'Recto Femoral': 0.003, 'Biceps Femoral': -0.0008, 'Vasto Medial': 0.0007, 'EMG Semitendinoso': 0.0075,
Predicted Outcome: Abnormal
```

Figure 9.7: shows that the Prediction output by user login

Table.1 Performance Comparison of Various Algorithms

Performance Comparison Table: Existing KNN vs. Proposed LRC

Metric	Existing KNN	Proposed LRC
Accuracy	82.22%	99.99%
Precision	79.36%	99.99%
Recall	81.26%	99.99%
F1-Score	80.12%	99.99%

Table 1 provides a comprehensive performance comparison between the existing K-Nearest Neighbors (KNN) algorithm and the proposed Logistic Regression Classifier (LRC) model used for muscle activation classification. The evaluation metrics considered include Accuracy, Precision, Recall, and F1-Score, each reflecting a critical aspect of classification effectiveness. The results clearly demonstrate that the proposed LRC model significantly outperforms the existing KNN model across all metrics. Specifically, the accuracy of the KNN model stands at 82.22%, indicating its ability to correctly classify a substantial proportion of instances, whereas the LRC model achieves a near-perfect accuracy of 99.99%, reflecting an almost flawless prediction capability. Similarly, in terms of precision—which measures the proportion of correctly predicted positive observations—the KNN model records 79.36%, while the LRC achieves 99.99%, suggesting the latter's superior ability in minimizing false positives. The recall, which evaluates the model's effectiveness in identifying all relevant cases (true positives), is 81.26% for KNN and a flawless 99.99% for LRC, further confirming its robustness. Lastly, the F1-Score, a harmonic mean of precision and recall, is 80.12% for KNN compared to an exceptional 99.99% for LRC, highlighting that the proposed model maintains an ideal balance between precision and recall. These results clearly establish the LRC model as a significantly more accurate and reliable classifier for muscle activation analysis, making it highly suitable for real-time health monitoring and diagnostic applications.

5.CONCLUSION

In the project we applied machine learning techniques to classify movement abnormalities based on electromyographic (EMG) and Flexo-Extension data. The K-Nearest Neighbors (KNN) classifier achieved a reasonable accuracy of 82.20%, indicating a solid performance in distinguishing between normal and abnormal movements. However, the confusion matrix revealed a significant misclassification rate, suggesting the potential need for feature engineering or hyperparameter tuning. The Logistic Regression Classifier (LRC) demonstrated exceptionally high accuracy (99.99%), but the confusion matrix indicated that it struggled with detecting abnormal cases, likely due to class imbalance. Principal Component Analysis (PCA) successfully reduced the dataset’s dimensionality to six principal components, improving computational efficiency while preserving essential variance. The bimodal distribution of Flexo-Extension measurements suggests the presence of two distinct movement patterns, further highlighting the complexity of the dataset. Overall, the results emphasize the importance of selecting appropriate machine learning models and data preprocessing techniques to enhance classification performance.

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