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A Comparative Study Investigating Machine Learning Methods for EMG Data Classification in Post-Stroke Rehabilitation

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Abstract **- Physiotherapy is essential for boosting recovery and enhancing quality of life after a stroke. Individualized therapies are required for stroke rehabilitation. This work explores machine learning techniques for electromyography (EMG) data classification in the context of post-stroke rehabilitation, which is important for comprehending and improving motor function. Our analysis covers a wide range of methods, such as Gradient Boosting (GB), Histogram-Based Gradient Boosting, Cat Boost, K-Nearest Neighbors (KNN), Decision Tree (DT), Random Forest (RF), Linear Discriminant Analysis (LDA), and LDA. We measure their performance using criteria like accuracy, precision, recall, and F1-score through a thorough evaluation procedure. Our results show that DT and RF perform consistently better than other algorithms, proving their reliability and effectiveness in the classification of EMG data. But KNN is equally promising, with relatively lesser precision than LDA. The work emphasizes how decision-based algorithms and ensemble methods may effectively classify EMG data, which has ramifications for improving stroke rehabilitation techniques. These discoveries can be used by scholars and professionals to further the creation of machine learning-based instruments for accurate gesture recognition in post-stroke rehabilitation.**

Keywords: Stroke Rehabilitation, EMG Data Classification, Machine Learning, Electromyography.

I. INTRODUCTION

The process of stroke rehabilitation is a multifaceted and intricate journey, involving various healthcare disciplines, with physiotherapy serving as a crucial component in enhancing bodily functions, structural integrity, daily activities, and overall participation in life [1]. What is paramount in this context is the implementation of personalized, evidence-based interventions, focused on promoting recovery, ensuring the continuity of care, and conducting rigorous studies with clinical benchmarks and patient-reported outcomes [2].

Stroke stands as the third most prominent contributor to adult disability on a global scale, casting a formidable shadow with an estimated 12.2 million newly diagnosed cases, 101 million ongoing cases, and a staggering 143 million disability-adjusted life years (DALYs) tallied in the year 2019 [3]. In the 1990s, substantial research efforts reshaped our understanding of how to optimize stroke care delivery, giving rise to comprehensive guidelines that span the spectrum from acute interventions to early rehabilitation within specialized stroke units [4].

The consensus across international healthcare communities is clear: multidisciplinary rehabilitation, inclusive of physiotherapy, consistently yields superior outcomes when compared to the absence of such rehabilitation efforts. Moreover, research underscores a positive relationship between the intensity of training received and the ultimate outcomes achieved [5]. Furthermore, evidence suggests a critical window of opportunity for recovery, extending primarily over the initial three to six months following a stroke, although this beneficial timeframe is by no means exclusive [6].

Despite significant strides, our grasp of the intricate biological and psychosocial components that facilitate stroke recovery remains incomplete (Bernhardt et al., 2020). Achieving optimal stroke rehabilitation remains akin to solving a multifaceted puzzle laden with uncertainties. In [7] aptly articulate the primary challenge faced by rehabilitation sciences – the imperative to bridge the gaps that exist between understanding mechanisms of neural plasticity, predicting outcomes, delineating the relationships between behavior and neurophysiological or imaging biomarkers, and crafting interventions that yield tangible, meaningful effects from the perspective of those directly affected by stroke [7].

Central to this endeavor are the concepts of meaning and motivation, which play pivotal roles in fostering compliance and are intrinsically tied to the neuroplasticity processes of recovery [8]. Beyond the invaluable insights garnered from neuroscience and clinical trials, there exists a pressing need

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for a framework that seamlessly integrates the subjective perspectives of individuals and places a keen emphasis on discerning what constitutes meaning alongside the conventional objective metrics in both research and clinical practice [8].

Disparities stemming from geographical and sociodemographic factors persist both in the availability and utilization of rehabilitation services [9]. Even within affluent nations, aligning with the recommendations of guidelines, which advocate for multidisciplinary organization and substantial post-stroke care, proves to be a formidable challenge when confronted with the complex dynamics of healthcare capacity and the imperative for efficiency [10].

It's noteworthy that while remarkable strides have been made in the realm of early stroke therapy, there's a risk that some of the gains achieved in short-term outcomes may erode over time due to unmet long-term needs [2]. Critics aptly argue that stroke, often approached as an acute condition, should be recognized as a chronic health challenge [11]. What becomes evident is the pressing need for a coordinated approach to immediate post-stroke follow-up, encompassing critical elements like physiotherapy, in order to ensure the continuity of care. Furthermore, there's a call for enhancing competency in neurological physiotherapy at the municipal level [11].

Interventions that build upon the current understanding of stroke recovery and emphasize the seamless continuation of care have the potential to mitigate fragmentation and elevate the overall quality of rehabilitation services [12].

In the field of physiotherapy, there are notable gaps in research when it comes to identifying the most effective approaches for mitigating post-stroke impairments. While broad recommendations supported by robust evidence favor an individualized, goal-oriented strategy, extensive training, and practice related to specific tasks [12], the literature reveals that several systematic reviews and meta-analyses pertaining to particular treatment methods remain inconclusive. This uncertainty largely arises from the limited quantity, subpar quality, or inconclusive nature of the trials conducted. Consequently, there is a clear call for evidence-based interventions that prioritize the goal of recovery [8].

These interventions must encompass measures designed to enhance and assess levels of physical activity and participation since these aspects often remain suboptimal even when an individual's functional recovery appears satisfactory [13]. Importantly, patients' perspectives on the quality of healthcare have gained prominence as crucial components of quality assessment, extending beyond standardized clinical outcomes [14].

Explorations into patient experiences following a stroke have shed light on novel dimensions of post-stroke disability. These encompass various facets of loss linked to bodily dysfunction and intertwined with aspects of identity, self-perception, and societal roles[15]. In this evolving landscape, emerging interventions should embrace the intricate nature of post-stroke disability by equipping patients with a holistic understanding of their post-stroke bodies, transcending the conventional biomedical division between the physical body and consciousness.

The integration of artificial intelligence (AI) holds immense promise within the context of this thesis and the field of post-stroke rehabilitation. AI technologies, such as machine learning and computer vision, have the potential to revolutionize the individualized and evidence-based approach to rehabilitation, as they can analyze vast datasets to identify personalized treatment plans tailored to a patient's specific needs and progress. Moreover, AI-driven predictive models can enhance our understanding of stroke recovery trajectories, helping clinicians anticipate patient outcomes more accurately. Furthermore, AI-powered tools can assist in monitoring and assessing patients' physical activity levels, compliance with therapy, and overall progress remotely, bridging geographical disparities in access to care. Additionally, the utilization of natural language processing in analyzing patient narratives and experiences can provide valuable insights for refining rehabilitation interventions, ensuring that they address not only physical but also psychosocial aspects of recovery. By incorporating AI into this thesis, we can unlock novel dimensions of stroke rehabilitation, promoting greater efficiency, personalization, and comprehensive care for stroke survivors.

II. RELATED WORKS

In [16], researchers address the limited clinical use of EMG-triggered neuromuscular electrical stimulation (EMG-NMES) for stroke upper limb recovery. They conduct a systematic review and meta-analysis, highlighting short-term improvements in motor impairment for chronic stroke patients.

Researchers in [17] proposes an innovative solution to address rehabilitation assessment limitations caused by therapists' experience reliance and infrequent assessments due to therapist availability constraints. They introduce an intelligent decision support system employing reinforcement learning to revolutionize the assessment process. This system autonomously identifies key assessment features, providing quantitative insights into patients' functional abilities, and streamlines assessments. The efficacy was evaluated involving seven therapists and a dataset of 15 patients performing three

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exercises. Results demonstrate the novel system's superiority over non-analytical methods, significantly enhancing therapist consensus (F1-scores from 0.6600 to 0.7108, $p < 0.05$).

Researchers in [18] propose an innovative solution for the intricate clinical aspects of stroke, spanning motor, language, sensory, and mental disorders. They recognize persistent post-treatment symptoms like numbness and paralysis, which could lead to permanent issues. With a focus on effective stroke rehabilitation, the researchers plan a model combining deep learning and electroencephalography (EEG).Their method involves preprocessing EEG signals, using an enhanced deep neural network(IDNN) for EEG classification. By drawing from large margin support vector machines (LM_SVM), the researchers enhance generalization, considering the complex aliasing in stroke data. Beyond EEG recognition, their approach integrates rehabilitation equipment control for patient assistance.

Researchers in [19] propose an innovative solution to the challenges posed by stroke, a major contributor to mortality and adult disability. Stroke results in motor loss, paralysis, and severe pain, necessitating intensive physiotherapy. They introduce an automated approach for efficient therapy exercise detection during rehabilitation. Their method involves a 3-Layer CNN-LSTM model, combining convolutional neural networks (CNN) and long short-term memory (LSTM) techniques. A physiotherapist-guided RGB camera captures a dataset, preprocessed for optimal use. Sequentially processing data through convolutional, fully connected (FC), and LSTM layers captures spatial and temporal dynamics. Empirical analysis highlights the 3-Layer CNN-LSTM model's supremacy, achieving 91.3% accuracy compared to CNN and KNN alternatives. This approach bridges the automated exercise detection gap in therapy. Enhancing the study's comprehensiveness, additional insights into dataset collection and physiotherapist involvement could be valuable. Empirical results robustly support the EEG classification model's superiority, highlighting practical value. While merging deep learning and EEG for stroke rehab is strength, more insights into EEG preprocessing and addressing implementation challenges could enhance the approach.

In [20], researchers explore robotic-based therapy for post-stroke motion recovery. They utilize myoelectric signals (EMG) for finger/hand motion identification, achieving successful dimensionality reduction and promising classification results.

Researchers in [21] aim to improve post-stroke rehabilitation using a motor imagery-based brain-computer interface (BCI) combined with virtual limbs and functional electrical stimulation (FES). They conduct a randomized study demonstrating greater motor function improvement in the BCI-FES group.

In [22], researchers propose a comprehensive upper-limb rehabilitation system incorporating EEG-based motion intent recognition and emotion classification. Their novel classifiers achieve significant accuracy improvements.

Researchers in [23] employ deep learning technology to design a stroke rehabilitation model based on EEG signals. They utilize an improved deep neural network model (IDNN) and large margin support vector machine (LM_SVM) to enhance EEG classification.

In [24], researchers focus on using error-related potentials (ErrPs) for upper-limb stroke patient rehabilitation. They achieve promising results in classifying ErrPs and suggest real-time assist-as-needed robotic therapy.

Researchers in [25] utilize error-related negativity (ERN) signals to enhance assist-as-needed robotic stroke rehabilitation. They identify a strong correlation between ERN signal amplitude and psychological/cognitive states, paving the way for adaptive rehabilitation.

Researchers in [26] propose PrimSeq, an innovative solution for quantifying functional motion doses in stroke rehabilitation. Amidst uncertainty about the optimal quantity for human recovery, PrimSeq integrates wearable sensors, deep learning motion prediction, and tallying algorithms. It accurately breaks down rehabilitation activities into elemental motions, excelling over alternative techniques. PrimSeq efficiently quantifies motions with precision, saving time and costs. Demonstrated on stroke patients, it offers potential for rigorous measurement and dosing trials support. Contributions include PrimSeq pipeline proposal, wearable sensors, and efficient quantification, with no identified deficits.

Researchers in [27] introduce an innovative solution for the limitations of stroke patient assessments – high time consumption, subjectivity, and imprecision. They develop an intelligent rehabilitation assessment system, uniting wearable devices and machine learning. Rigorous evaluation against clinical Fugl–Meyer assessment (FMA) showcases strong correlation ($R2 = 0.9667$) and consistent scores. Notably, 92.50% and 95.83% of deviations remain within acceptable ranges. The system outpaces clinician assessment in speed, with a 35.00% reduction. Contributions include proposing an intelligent wearable system, validating accuracy through FMA comparison, and highlighting time savings. No specified deficits identified.

Researchers in [28] propose leveraging AI and patient data for personalized stroke outcome predictions. Recent

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stroke treatment advancements have reshaped care. Their review outlines AI's potential across acute, subacute, and chronic stages, covering diverse data types and discussing pros and cons. Emphasis is on AI's methodological significance for precision medicine. Contributions include AI's revolutionary potential, data type coverage, and exploration of its pros and cons. No specified deficits.

III. METHODOLOGY

The overall model block diagram in Figure (1) shows the steps that go into training and assessing a logistic regression classifier for the categorization of EMG (Electromyography) data. The EMG data is first loaded into the diagram from a CSV file, and then a portion of the data is sampled for training. Next, the sampled data is used to extract the features (time and channel readings) and labels (classes). If needed, the class labels are then encoded into numerical values. After that, the data is divided into training and testing sets, and to guarantee uniformity, the input features are standardized. These standardized training data are used to develop and train a logistic regression model. In order to evaluate the trained model's performance, test data is used to generate a confusion matrix and a classification report. In the end, a flowchart representing the complete procedure and the confusion matrix plotted as a heatmap are presented to make the workflow easier to grasp.

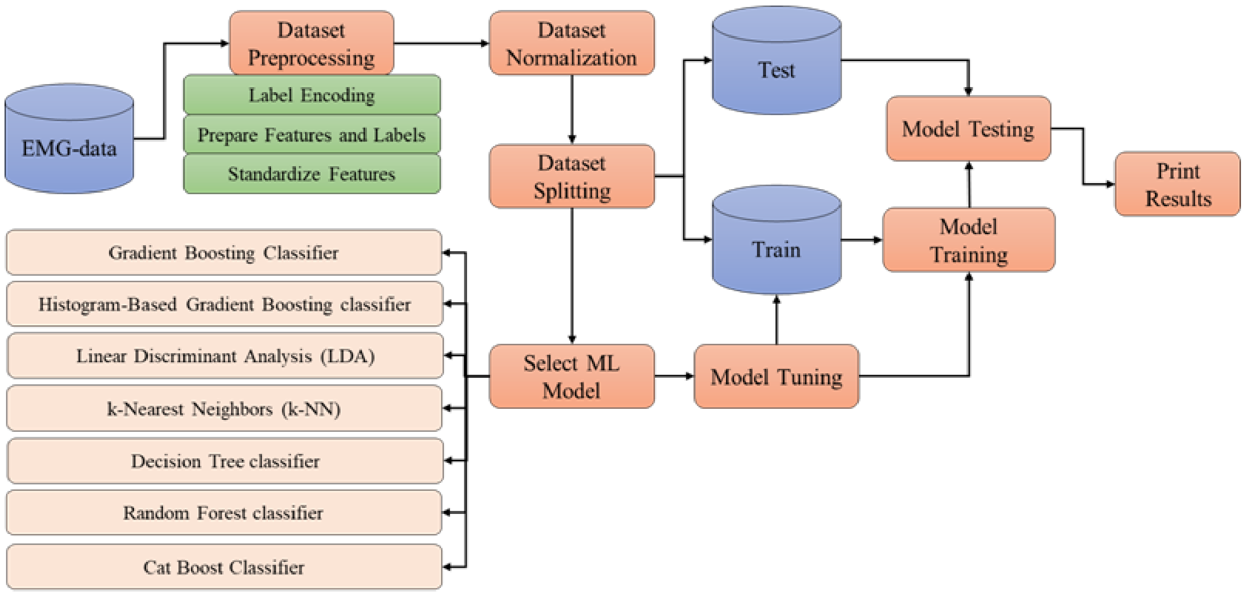

Figure 1: Overall Model Block Diagram

A) Dataset Description

The dataset is made up of 36 subjects' raw EMG (Electromyography) data that was obtained via a Bluetooth-enabled MYO Thalmic bracelet that was worn on the forearm. Every participant made a sequence of six or seven fundamental hand movements in each series. Every gesture was performed for three seconds, with a three-second break in between each movement. Ten columns make up the dataset: the first one shows the time in milliseconds, and columns two through nine show the EMG readings from the bracelet's eight sensors. The label of the motions is shown by the tenth column, "Class," where 0 indicates unmarked data and integers 1 through 7 correspond to particular hand gestures, such as held at rest, fisted hand, wrist flexion, wrist extension, radial deviations, ulnar deviations, and extended palm. Furthermore, a column labelled "label" is appended to identify the individual(s) that carried out the experiment; each subject made the motions twice. Researchers and practitioners working in the subject of gesture detection and classification will benefit greatly from this analytics-ready dataset, which allows them to explore different machine learning algorithms and strategies for precise gesture identification.

B) Dataset Preprocessing

Preprocessing techniques were used to the dataset before the machine learning model was trained. Initially, the LabelEncoder from the scikit-learn module was used to encode the class labels into numerical values if they were in string format. This guarantees consistency in the way class labels are represented. The input features were then normalized to have a standard deviation of 1 and a mean of 0. Regardless of their initial scales, all features contribute equally to the model training process thanks to this method, which makes use of the StandardScaler from scikit-learn. To be more

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precise, the training features (X_train) were transformed to have the required distribution by fitting them to the scaler, and the testing features (X_test) underwent the same transformation to preserve consistency in scaling across the two datasets. Standardizing the features improves the machine learning model's stability and convergence, which in turn improves how well it predicts the target variable.

C) Select Machine Learning Model

Gradient Boosting Classifier: Gradient Boosting is an ensemble learning strategy that minimizes the loss function by adding weak learners (usually decision trees) one after the other until a strong prediction model is created. Its main objective is to minimize errors by optimizing the loss function's gradient. With each new tree, the mistakes of the preceding ones are fixed, creating a strong ensemble model that can handle intricate datasets and have a high degree of predicted accuracy[29].

Histogram-Based Gradient Boosting Classifier: Instead of using individual data points, this Gradient Boosting variation creates decision trees based on input feature histograms. To expedite the training process, it discretizes the feature space into bins and computes histograms. It is appropriate for large datasets with numerous features since it minimizes the computational overhead involved in splitting nodes in decision trees by binning the data[30].

Linear Discriminant Analysis (LDA): One dimensionality reduction method for classification tasks is LDA. It looks for linear feature combinations in the dataset that best distinguish between various classes. It minimizes the within-class variance andmaximizes the between-class variance while projecting the data into a lower-dimensional space. According to LDA, the classes' covariance matrices are the same and the features are assumed to be regularly distributed[31].

k-Nearest Neighbors (k-NN): An instance's class label is assigned via the non-parametric classification method k-NN based on the majority class of its k nearest neighbors in the feature space. It works well for both linear and non-linear decision limits and makes no assumptions about the distribution of the underlying data. However, when dealing with noisy or high-dimensional data, its performance could suffer[32].

Decision Tree Classifier: Based on feature values, decision trees are flexible and comprehensible classification models that divide the feature space into discontinuous parts. Every leaf node represents a class label, and every internal node represents a judgement based on a feature. Overfitting is a common problem with decision trees; however, it can be lessened with methods like Random Forest and pruning[33].

Random Forest Classifier: During training, a large number of decision trees are built using the Random Forest ensemble learning technique, which yields the mean prediction (regression) or the mode of the classes (classification) for each tree. By decreasing overfitting and raising predictive accuracy through bootstrapping and feature randomness, it outperforms the single decision tree in terms of performance[34].

Cat Boost Classifier: A gradient boosting library called Cat Boost is designed primarily to handle categorical features well. To increase training speed and prediction accuracy, it uses methods like ordered boosting and oblivious trees. Widely applicable to a variety of classification applications, Cat Boost automatically handles categorical data without the need for preprocessing and is resistant to overfitting[35].

D) Models Tuning

With a maximum depth of three levels and a learning rate of 0.1, the Gradient Boosting Classifier is set up with 100 estimators (decision trees) that will be added one after the other over the course of training. In order to guarantee reproducibility of results over multiple runs, the Random State parameter is set to 42. The model is trained with a maximum of 100 iterations for the Histogram-Based Gradient Boosting classifier, and 42 random states are included for consistency. The shrinkage parameter in Linear Discriminant Analysis (LDA) is set to 'auto' to decide the amount of shrinkage automatically, while the solver is set to 'lsqr', indicating the solver to use for the optimization issue. Furthermore, LDA is set up to reduce the data's dimensionality to ten components. There are five neighbors that the k-Nearest Neighbors (k-NN) algorithm takes into account when classifying data. To guarantee deterministic behavior during training, the random state for both the Random Forest and Decision Tree classifiers is set to 42. Lastly, a random state of 42 is used to initialize the CatBoostClassifier, guaranteeing repeatability of results and steady performance over several runs. Each algorithm can efficiently learn from the training data and produce precise predictions while preserving stability and repeatability thanks to these parameter choices. Table (1) shows the algorithms parameters.

Table 1: Selected Algorithms Parameters

Algorithm	Parameters	
Gradiant Boosting Classifier	N-Estimation	100
	Learning Rate	0.1
	Max Depth	3
	Random State	42
Histogram-Based Gradient Boosting classifier	Max Iteration	100
	Random State	42
Linear Discriminant	solver	Lsqr

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Analysis (LDA)	shrinkage	Auto
	N-Components	10
k-Nearest Neighbors (k-NN)	N_Neighbors	5
Decision Tree classifier	Random State	42
Random Forest classifier	Random State	42
CatBoostClassifier	Random State	42

E) Evaluation Metrics

The assessment scale is essential for training a classifier in order to obtain the best classifier feasible. Therefore, in order to differentiate and obtain the best classifier, choosing the appropriate rating scale is essential. To improve the generative classifier, relevant assessment metrics that are meant to serve as discriminators have been carefully examined in this section. In general, many generative classifiers use accuracy as a metric to determine which training solution is optimal. There are a number of disadvantages to accuracy, such as less discriminatory, less informative, and biassed data against data from the dominant class. This paragraph also includes a brief discussion of other measurements that are specifically meant to establish the optimal solution. The disadvantages of these other measures are also mentioned[36].

Figure (2) shows the confusion matrix for a binary classifier. Positive (1) and Negative (0) are the expected values, whereas True (1) and False (0) are the actual values. Expressions in the confusion matrix, such as TP, TN, FP, and FN, are used to estimate the potential of categorization models. [37].

Class designation		Actual class	
		True (1)	False (0)
Predicted class	Positive (1)	TP	FP
	Negative (0)	FN	TN

Figure 2: Binary Classification Confusion Matrix

- **TP (True Positive) -** The data of interest in the disarray framework is the genuine positive point (TP) when a positive result is normal and exactly the same thing occurs.
- **FP (False positive) -** The data of interest in the disarray lattice is a bogus positive when a positive outcome was normal, and what happened is an adverse outcome. This situation is known as a sort 1 mistake. It resembles the gift of awful premonition.
- **FN (False Negative) -** The data of interest in the disarray lattice is bogus negative when an adverse result was normal, and what happened is a positive result. This situation is notable as a kind 2 blunder and is considered as perilous as a sort 1 mistake.
- **TN (True Negative) -** The data of interest in the disarray framework is Valid Negative (TN) when an adverse result is normal and the equivalent occurs.

Table 2: The elements of the evaluation process (variables, definitions, and equations)

Variable	Definition	Equation
Accuracy	The percentage of accurately anticipated data from tests is easily determined by dividing all accurate forecasts by all predictions.	$Accuracy = \frac{Tp + TN}{TP + TN + FP + FN}$
Precision	The proportion of outstanding instances among all anticipated ones from a specific class	$Precision = \frac{TP}{TP + FP}$
Recall	The ratio of the total number of occurrences to the proportion of instances that were supposed to be members of a class	$Recall = \frac{TP}{TP + FN}$
F1-Score	The phrase is used to describe a test's accuracy. The maximum F1-score is 1, which denotes outstanding recall and precision, while the lowest F1-score is 0.	$F1 - Score = 2 \times \frac{percision \times recall}{Percison + recall}$

IV. RESULTS

The performance study of the algorithm in Table (3) shows significant differences between models. The best performers are Decision Tree (DT) and Random Forest (RF), both of which have outstanding results in all measures. RF stands out for having a particularly high accuracy rate of 95%. Strong performance is also shown by K-Nearest Neighbors (KNN), whose accuracy and F1-score are more than 80%. With lower precision scores, Linear Discriminant Analysis (LDA) falls behind. With accuracy ranging from 67% to 75%, Gradient Boosting (GB), Histogram Gradient Boosting (Hist GB), and Cat Boost exhibit decent performance. Cat Boost has the lowest precision of all of them. All things considered, Random Forest (RF) is the most dependable option; it regularly performs well in all evaluation criteria, which makes it a solid contender for additional research or real-world use.

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Table 3: Models Evaluation Metrics

Algorithm	Accuracy	Precision	Recall	F1-Score
GB	67	56	67	64
Hist GB	70	68	70	68
LDA	64	41	64	50
KNN	81	80	81	80
DT	94	94	94	94
RF	95	95	95	95
Cat Boost	75	70	72	70

Some important findings are highlighted by the algorithms' performance analysis. Random Forest (RF) and Decision Tree (DT) score better on all criteria, proving to be robust and efficient in the task at hand. Their balanced precision, recall, F1-score, and high accuracy make them dependable options for classification tasks. Though it does not perform as well as DT and RF, K-Nearest Neighbors (KNN) also demonstrates its capacity to recognize patterns effectively. The precision of Linear Discriminant Analysis (LDA) is relatively lower, suggesting that it may be difficult to accurately detect positive cases. There is potential for increase in precision and F1-score for Gradient Boosting (GB), Histogram Gradient Boosting (Hist GB), and Cat Boost, as they demonstrate reasonable performance. Overall, the findings indicate that decision-based models like Decision Trees and ensemble approaches like Random Forest are appropriate for the current classification problem, however additional testing and optimization may improve the efficiency of alternative algorithms.

V. CONCLUSION

There are notable differences in the efficiency of different algorithms when it comes to classifying EMG data, as shown by their performance analysis. The best performing algorithms are Decision Tree (DT) and Random Forest (RF), which show excellent results in terms of accuracy, precision, recall, and F1-score, among other evaluation metrics. They are dependable options for classification tasks because of their resilience and well-rounded performance. With lower precision scores, Linear Discriminant Analysis (LDA) performs worse than K-Nearest Neighbors (KNN), which also performs well. While Cat Boost, Histogram Gradient Boosting (Hist GB), and Gradient Boosting (GB) exhibit moderate performance, there is room for improvement in F1-score and precision. the results point to the suitability of ensemble approaches and decision-based models for the classification of EMG data; nevertheless, additional research and optimization could improve the efficiency of other strategies. Researchers and practitioners looking to use machine learning approaches for accurate gesture identification and categorization in EMG data analysis will benefit greatly from these findings.

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