Detecting Various Hand Gestures from EMG Signals Using Inkjet-printed Dry Flexible Electrodes with Machine Learning Algorithms

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Abstract*—The Electromyography (EMG) signals are one of the most used biological signals which are essential for identifying muscular abnormalities that cause a variety of diseases. Many contemporary technologies are utilized to examine muscle activities through EMG signals. This paper describes a novel dry EMG electrode fabricated with the inkjet-printing (IJP) technique of silver (Ag) nanoparticles on flexible polyamide (PI) film. The design is made up of basic electronic components that are affordable and easy to find. Current research on EMG-based movement classification encounters difficulties with inaccurate classification, lacking generalization ability, and poor robustness. This paper discusses the classification of EMG signals by creating and optimizing various machine-learning models to tackle these issues. For the recognition of different hand gestures based on EMG signals, we focus mainly on 3 areas: First, the preprocessing of the EMG signal obtained from the IJP electrodes, the next area is the extraction of various features in the time domain, finally the recognition of the gestures in the signals using the following classifiers: SVM (Support Vector Machine), Random Forest (RF), Decision Tree (DT) and Artificial Neural Network (ANN). We assessed the ML models' performance using a dataset containing 38,759 sample values. The RF model in the proposed system reached a top accuracy of 99%. The outcomes of the other classifiers were as follows: Artificial Neural Network (97%), Decision Tree (94%), and Support Vector Machine (90%). This suggested approach is very precise and cost-effective for clinics, making it a possible tool for clinical support in diagnostics and resource optimization.

Keywords: EMG signals, muscle activity, EMG sensors, IJP electrode, feature extraction, machine learning model

I. Introduction

The surface electromyography (sEMG) signal is a group of potential changes recorded on the skin surface while muscles contract, indicating neuromuscular activity [1]. Intelligent prosthesis control, rehabilitation therapy, and clinical diagnosis all greatly benefit from the noninvasive surface EMG signal detecting technique. An EMG signal represents the muscle's electrical activity through a voltage versus time graph obtained by placing electrodes on the skin. The voltage of sEMG signals typically falls within the -5 to +5 mv range and is mostly concentrated between 50 and 150 Hz. Electrodes pick up subtle electrical fluctuations, which the outcomes of muscle depolarization and repolarization occur after each movement. Gathering EMG signals produced by the human body with electrodes is now a common practice in both rehabilitation engineering and medical research.[3]. There has been a growing emphasis on the advancement of EMG-based control in order to enhance the quality of life and social acceptance of the disabled and elderly populations in recent years. EMG devices have been redesigned to prioritize patient comfort and can now be remotely monitored outside of healthcare facilities without disrupting daily tasks due to advancements in technology.

The field of flexible electronics is expanding with a range of uses, including biomedical sensors, wireless communication, and more. This technology shows great promise because it can adapt to various shapes and is cost-effective [4]. Flexible electronic sensors have the potential to improve user comfort and enable earlier disease detection for remote monitoring, resulting in more efficient medical services due to their reusability. Traditional fabrication process uses a rigid substrate. But flexible electronics devices are fabricated on flexible substrates and can be easily created to become worn comfortably in any chosen location. Inkjet Printing (IJP) technology stands out as an appealing choice as it enables the creation of electronic circuits on surfaces like paper, glass, polyamide film, and more. The wet gel electrode commonly used in clinical settings is typically seen as the standard electrode for assessing EMG signals. They use a gel of Ag/AgCI to get better skin-electrode coupling In the gel electrode.However, the gel electrode is single-use and not designed for extended use. Numerous users complained of skin irritation and discomfort caused by the gels and adhesives that come in contact with the skin[5]. Inkjet-printed (IJP) electrodes offer a low-cost and promising solution for efficient EMG signal analysis in modern healthcare, reducing the issues associated with wet gel electrodes. They are designed to be thin, flexible, and conformable to the body, ensuring a more comfortable experience for users, even during prolonged wear. Dry electrodes improve as time goes on because more moisture seeps into the skin-electrode interface, leading to better coupling. Dry electrodes ensure high signal quality and reliability with strong adhesion, excellent physical stability, extensive effective area, and thin yet highly flexible construction.[6].

Categorizing EMG signals based on their various application is the most difficult aspect of creating interfaces that utilize myoelectric control. This could be due to the differences in EMG signal features, which vary based on factors such as age, muscle activity, motor unit pathways, skin-fat layer, and movement style. Extracting different features from EMG signals obtained from the muscles of amputees or disabled individuals can be challenging at times. For accurate classification of EMG signals for various hand gestures, the implementation process includes three steps in sequence: data pre-processing, extraction of features, and categorization [7]. Nevertheless, EMG signals can be affected by external factors like electrode displacement and muscle tiredness, even slight alterations can significantly influence classification outcomes.

In this study, we designed and fabricated flexible IJP EMG electrodes to develop a cost-effective EMG signal acquisition system to collect muscle activity for different hand gestures. Utilizing the flexibility and accuracy of IJP technology, we could develop electrodes that provide comfort to the skin, guaranteeing both reliability and ease of use. The purpose of this paper is to assess the effectiveness of utilizing EMG data in distinguishing between various hand gestures. To classify various motions and determine the user's state, we utilized different machine learning algorithms and evaluated the accuracy outcomes to establish the superior one. Our new system can help understand the patient's muscle condition and abnormalities by analyzing the EMG signals, which helps doctors to take early steps in healthcare awareness.

II. Experimental Setup

A. Ag 191 Ink

We have used the silver ink Ag 191 for our IJP electrodes whose product name is silver nanoparticle (AgNP) ink, Metalon® JS-A191. Novacentrix Inc., TX, USA is the manufacturer of this commercial Ag 191 ink. This ink is composed of 40% silver nanoparticles by weight, featuring a silver concentration ranging from 25% to 50%. It includes 10-15% ethylene glycol and 0.2 – 1% polyethylene glycol 4-(tert-octylphenyl) ether as part of its formulation. At 25°C, the ink exhibits a viscosity ranging from 8 to 12 cP, and its surface tension falls between 28 to 32 dyne/cm. The average particle size (Z-avg) of JS-A191 ink is between 30 and 50 nm, with a specific gravity of 1.6.

B. IJP Fabrication Process

To capture real-time EMG data, we created dry EMG electrodes on flexible polyamide films using Inkjet Printing (IJP). The fabrication process involved utilizing a PC-controlled Dimatix Materials Printer (DMP-2850, FujiFilm Inc., USA) equipped with a MEMS-based printer cartridge containing 12 linearly arranged printing nozzles with 338.67 μm gaps, with the cartridge head angle set at 2.5°. This results in a 15 μm drop spacing at a printing resolution of 1693 dpi. We have used the polyamide film substrate as the base for our production process. Before starting the fabrication process it was wiped with isopropyl alcohol to eliminate any dust. Subsequently, the ink JS-A191 was injected into the substrate using the DMP printer to create the conductive layer.

During the IJP process, the ink is released drop by drop from the nozzle of the cartridge in a printing direction from left to right onto the polyamide substrate. After printing, we cured it at 180 temperature for 20 minutes. The choice of Metalon® JS-A191 silver nanoparticle (AgNP) ink was driven by its high conductive properties and compatibility with polyamide. We used an anchoring cavity construction technique to improve substrate adherence and boost the reusability of large-area traces, such as pads. The printed layers contain deliberate gaps created by these holes. These spaces are meant to relieve the thin-film remnants of stress. They successfully lessen the possibility of surface stress mismatch between the printed thin-film and substrate, which lowers the risk of adhesion-related problems like delamination and attachment to the body. This method guarantees that the traces will remain functional and intact even after numerous uses.

C. Layouts of IJP Electrodes

In Fig. 1 the layouts of our designed IJP electrode are shown. It is rectangular. These layouts have been created with InkScape software. Then the image was exported in PNG format at 1693 dpi resolution. The irfanView program changed the PNG images to a 24-bit-bmp type. Next, we utilized the MS Paint program to change these pictures into monochrome bmp style.

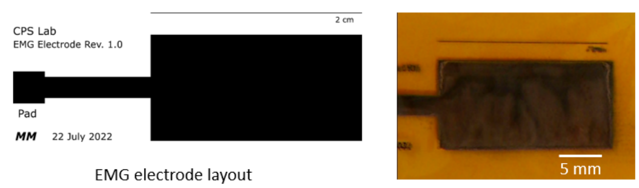

Fig. 1. (Left) Proposed IJP EMG electrode layout design. (Right) An IJP fabricated EMG electrode.

D. System Overview

To capture the EMG signals, three IJP electrodes are positioned on the hand muscle. The signal captured falls within the mV range and includes a variety of signals from body parts other than muscles. The method of acquiring the EMG signal from the hand muscle is shown in Fig. 2.

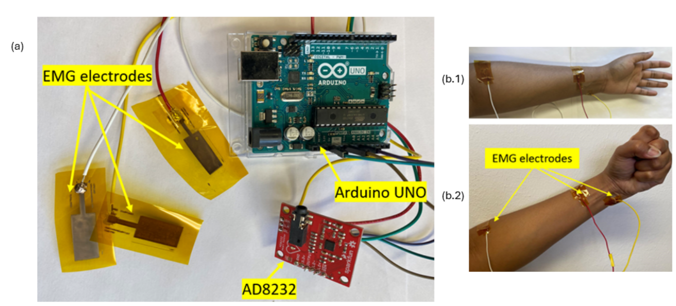

Fig. 2. a) Circuit setup for EMG signal acquisition b) Examples of different hand positions 1) Relax hand position 2) Hand Stretch position

The main elements used were an ATmega 328 microcontroller linked to an MPU-6050 module. MPU-6050 have applications like the IMU sensor in this study. It contains a unit with 6 separate analog-to-digital converters (ADCs) that includes a 3-axis accelerometer and a 3-axis gyro meter. One AD8232 chip was connected through connecting wires to ATmega328 and three electrodes were connected to the microcontroller from the muscle. The sensor values were collected from the MPU-6050 sensor and then saved in a CSV file.

III. Methodology

A. Data Acquisition

We have collected 7 participants' (Age range: 25-35 years old) EMG data at a 100 Hz sampling rate for various hand gestures for the duration of 13 minutes each. To ensure an organized data collection, Our data collection protocol involved a series of different hand gesture steps. The steps are as follows:

1) Place the electrodes and keep the hand in a still and relaxed position for 20 seconds.
2) Then bend the wrist to the right (open palm) for 10 seconds and then bend the wrist to the left (open palm) for 10 seconds.
3) After that, again keep the hand in a still and relaxed position for 10 seconds and straight hand with fist for 10 seconds.
4) Then, bend wrist to the right (with fist) for 10 seconds and then bend wrist to the left (with fist) for 10 seconds.
5) Again keep the hand in a still and relaxed position for 10 seconds.
6) Then, stretch the hand for 20 seconds.
7) At last, keep the hand in a still and relaxed position for 20 seconds.
8) Then we saved our all EMG data in a CSV file in our working PC.

B. Data Visualization

Figure 2 (b) illustrates a useful arrangement of a user with the electrodes placed on the hand muscles. We used 2 types of EMG electrodes for real-time EMG data collection. These Electrodes are commercial gel electrodes (Red Dot Electrodes 2560, 3M, Maplewood, MN) and our fabricated IJP electrodes. The collected signals from the user 1 are plotted in Fig. 3 to compare both signals. In order to determine the signal-to-noise ratio (SNR) [8] of the EMG signal we collected, we employed the following calculation:

$$\mathrm{SNR} = 10 \log \left(S/N \right)$$

S represents the signal power in its original form while N represents the power of the noise. The SNR for gel and IJP electrode were 18.97 dB and 18.94 dB respectively for user 1. We also calculated the SNR for other users to compare the results.

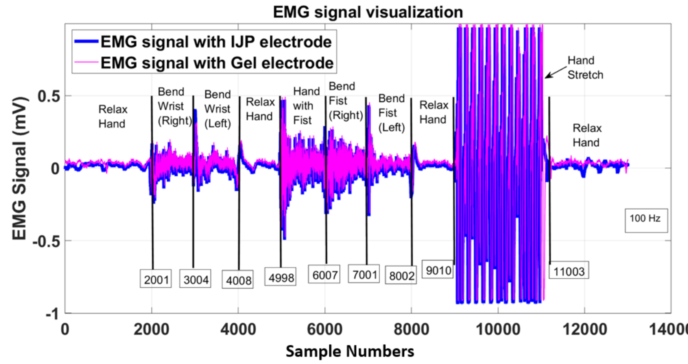

Fig. 3. Data visualization of EMG signal using IJP electrode and gel electrode

C. Feature Extraction

Feature extraction from unprocessed data is an essential phase in data analysis. Our research consisted of gathering 50 batches of EMG signal information while capturing different hand gestures from multiple participants at a sampling rate of 100 Hz. In this study, we gathered various features from all the datasets we collected. The features that were obtained were divided into three groups: temporal, spectral, and statistical. 145 signal-independent features were derived by utilizing Time series feature extraction library (TSFEL) [9], a python package designed for analyzing time series data. Main extracted features are outlined in Table I. Fig. 4 shows the flow diagram of the overall classification process.

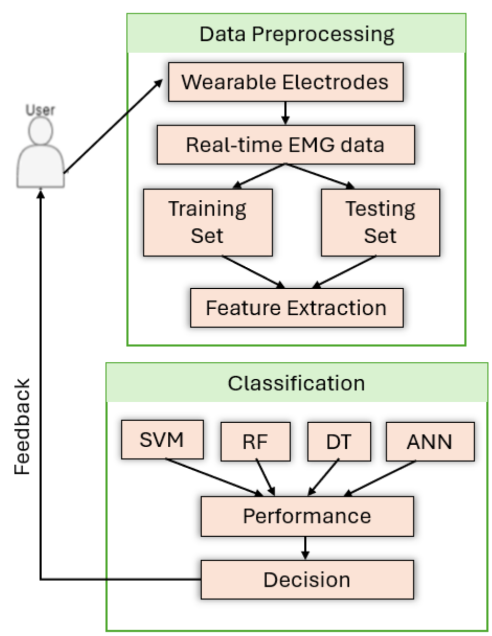

Fig. 4. Flow diagram for processing, analyzing, and classifying EMG signals using machine learning algorithms.

TABLE I
MAIN FEATURES EXTRACTED FOR MACHINE LEARNING ALGORITHM

Features	
0_Absolute energy	0_Fundamental frequency
0_Area under the curve	0_Kurtosis
0_Centroid	0_Human range energy
0_ECDF_3	0_Max power spectrum
0_ECDF_7	0_Mean absolute deviation
0_FFT mean coefficient_0	0_Mean absolute diff
0_Histogram_2	0_Median frequency
0_Histogram_5	0_Spectral positive turning points
0_Histogram_8	0_Peak to peak distance
0_FFT mean coefficient_9	0_Root mean square

D. Model Training

In order to ensure accurate detection and compare the outcomes, we analyzed our dataset using 4 machine learning models. The Support Vector Machine (SVM), Random Forest (RF), Decision Tree (DT), and Artificial Neural Network (ANN) are included. Model training is crucial for a classifying task because it is the process through which a machine learning model learns from the provided data to make accurate predictions or classifications on new data [10].

For training, we split our dataset into 2 types of groups. The dataset was split into a training set of 80% and a testing set of 20% in the initial group. For our second method, we divided the complete data into three separate sections: the training set, the validation set, and the testing set, with proportions of 70%, 15%, and 15% respectively. This enables us to assess our model with a separate testing set and confirm its performance while training.

The study's goal was to create a custom EMG recognition model, so we concentrated on assessing each model's performance. Hence, we utilized a 10-fold cross-validation on all models to minimize the variability in performance evaluations. Once we trained our dataset with the optimal parameter settings for all three dataset distributions, we calculated accuracy and performance metrics. Table II displays a list of crucial parameters of the models.

TABLE II
KEY PARAMETERS OF DIFFERENT MACHINE LEARNING MODELS

Classifier	Combination of hyperparameter
SVM	SVC (kernel='rbf', C =0.3, gamma ='scale'
RF	Number of trees=100 , max_depth=8, criterion = 'entropy'
DT	Max_depth = 7 , random_state= 'none'
ANN	Optimizer = 'SGD', three layers of neurons

IV. RESULTS

Different hand gestures collected from the datasets are regarded as different classes which are shown in the following Table III.

In Table IV we have provided the specifics of the computer where all the algorithms were computed to compare the performance metrics accurately. Table V presents the results of different ML models, showcasing training and testing accuracy, along with error metrics such as Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), R-squared, and Mean Log Squared Error (MLSE) [12], for different dataset distributions. Based on the results we calculated, we can conclude that RF had the top performance. Figures 5, 6, 7, and 8 show the comparison between predicted and true class distributions for 4 models in 10-fold cross-validation where they excel.

TABLE III
DIFFERENT CLASS LIST

Position	**Target class**
Hand in still and relax position	Relax Hand
Bend wrist to the right (open palm)	Wrist Right
Bend wrist to the left (open palm)	Wrist Left
Straight hand with fist	Fist
Bend wrist to the right (with fist)	Fist Right
Bend wrist to the left (with fist)	Fist Left
Hand stretch	Stretch

TABLE IV
SPECIFICS OF THE COMPUTER WHERE ALL THE ALGORITHMS WERE COMPUTED

Specifics	**Information**
OS Name	Microsoft Windows 11 Home
Version	10.0.22631 Build 22631
System Manufacturer	SAMSUNG ELECTRONICS CO., LTD.
System Model	930XDB/931XDB/930XDY
System Type	x64-based PC
Processor	11th Gen Intel(R) Core(TM) i7-1165G7 @ 2.80GHz, 2803 Mhz, 4 Core(s), 8 Logical Processor(s)
Installed Physical Memory (RAM)	8.00 GB
Disk Type	SSD
Swap Size	15817MB

Table VI presents the precision, recall, and f1-score for different models for 10-fold cross-validation split group. Based on these metrics also, the RF classifier shows the most promising results and is a suitable choice for our purpose. The RF classifier also minimizes the uses of time resources and memory consumption of the system. Table VII shows the time and memory consumption levels for different models for different dataset setups which shows that the RF model is more effective.

V. DISCUSSION

We designed flexible EMG electrodes with Ag nanoparticle ink on polyamide films in a rectangular shape for this study. We additionally gathered real-time EMG data with our produced IJP electrodes and compared the signals with that of gel electrodes available. We gathered the data at the same time with both the elctrodes enabling precise comparison of data. Our fabricated EMG electrodes displayed nearly similar SNR and coherence as gel electrodes. The flexibility and extended wear of IJP electrodes outperformed gel electrodes.

TABLE V

PRESENTATION OF PERFORMANCE METRICS FOR VARIOUS MODELS ON DIFFERENT DATASET SPLITS ACROSS A RANGE OF HAND GESTURES

	Dataset with 80/20 split				Dataset with 70/15/15 split				10-fold cross validation			
	SVM	RF	DT	ANN	SVM	RF	DT	ANN	SVM	RF	DT	ANN
Training set accuracy (%) ↑	86	96	94	95	89	98	94	97	90	99	94	98
Testing set accuracy (%) ↑	85	95	93	94	89	98	94	96	90	98	94	97
RMSE ↓	0.94	0.33	0.41	0.66	0.84	0.36	0.45	0.53	0.79	0.2	0.41	0.44
MAE ↓	0.31	0.04	0.08	0.14	0.24	0.05	0.1	0.09	0.22	0.02	0.08	0.05
R-squared ↑	0.84	0.96	0.95	0.92	0.87	0.98	0.96	0.95	0.89	0.99	0.97	0.97
MLSE ↓	0.07	0.01	0.02	0.03	0.06	0.01	0.02	0.02	0.05	0	0.02	0.02

TABLE VI

PRESENTATION OF DIFFERENT MODELS' PRECISION, RECALL, AND F1-SCORE FOR 10-FOLD CROSS-VALIDATION SPLIT FOR DIFFERENT HAND GESTURES

	SVM			RF			DT			ANN		
	Precision	Recall	F1-score	Precision	Recall	F1-score	Precision	Recall	F1-score	Precision	Recall	F1-score
Relax Hand	1	1	1	1	1	1	1	1	1	0.99	1	1
Wrist Right	0.6	0.62	0.61	1	0.93	0.96	0.73	0.83	0.78	0.92	0.94	0.93
Wrist Left	0.68	0.78	0.72	1	1	1	0.96	0.81	0.88	0.9	0.89	0.89
Hand with Fist	0.87	0.84	0.85	0.98	0.98	0.98	0.83	0.71	0.77	1	0.98	0.99
Fist Right	0.77	0.86	0.81	0.94	1	0.97	0.79	0.95	0.86	0.99	1	0.99
Fist Left	0.85	0.65	0.74	1	1	1	0.99	0.96	0.97	0.95	0.94	0.95
Hand Strech	1	1	1	1	1	1	1	1	1	1	0.98	0.99

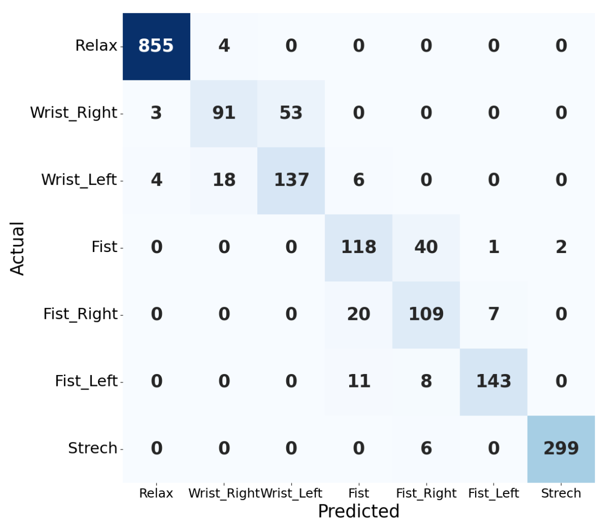

Fig. 5. Actual class and predicted class presentation for SVM model utilizing a 10-fold Cross Validation split

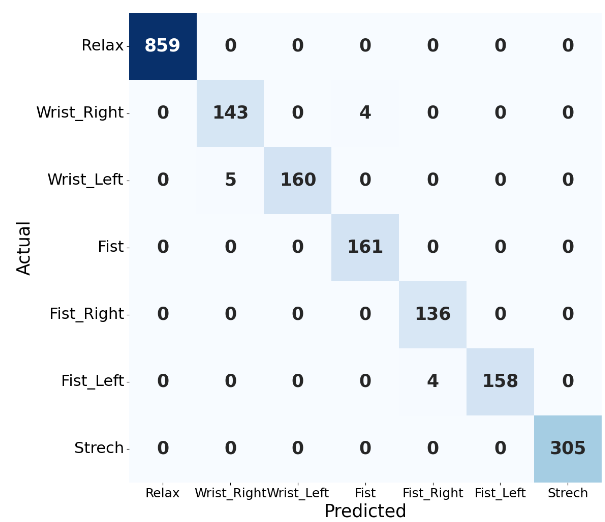

Fig. 6. Actual class and predicted class presentation for RF model utilizing a 10-fold Cross Validation split

Our study's findings indicate that the RF model is superior to all other models in classifying various hand gestures with the dataset. In all of our experiments, the RF model has consistently demonstrated superior performance with an accuracy rate as high as 99%. RFs are extremely flexible and can manage enormous and intricate datasets containing millions of observations and thousands of features. Utilizing bagging and feature randomness in the algorithm's ensemble approach assists in decreasing overfitting and improving overall performance through generalization.

However, the SVM does not perform well with our large dataset. Expansive datasets can make the SVM challenging, especially when there is a lot of noise and outliers present. SVM may require a significant amount of time to process large datasets, especially if the data is not well separated or the feature space is intricate.

VI. CONCLUSION

EMG signals have various applications, notably in prosthetic devices and rehabilitation fields. The outside surroundings can easily interfere with those signals, causing them to lose crucial information. To overcome these problems an approach to design an EMG signal acquisition system using IJP dry EMG electrodes on flexible polyamide films, which is a low-cost manufacturing technique from users' muscles is presented in

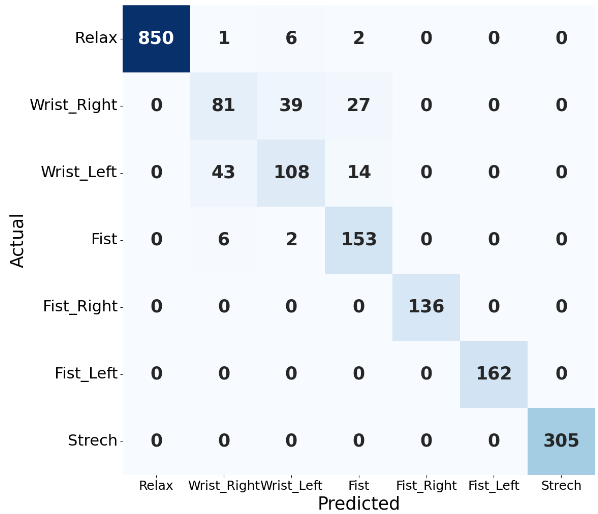

Fig. 7. Actual class and predicted class presentation for DT model utilizing a 10-fold Cross Validation split

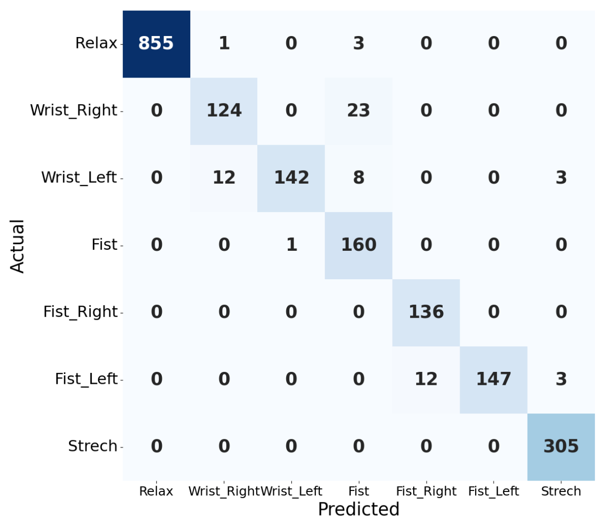

Fig. 8. Actual class and predicted class presentation for ANN model utilizing a 10-fold Cross Validation split

this paper. The aim of this EMG system is to assist individuals in monitoring their muscle strength level and obtain valuable muscle signals for purposes of rehabilitation. After gathering data, the process of feature extraction was conducted to obtain valuable insights from the signal to get it ready for classification. Supervised methods, such as SVM, RF, DT, and ANN, are employed in this phase for the classification of EMG signals. The experimental result was processed and compared with each other in terms of different performance metrics. Through experimentation and comparing performance with various types of datasets, it was discovered that the RF model was superior to other models across all three datasets. Our suggested method could improve the effectiveness of machine learning models for disease identification by minimizing error rates. By analyzing these EMG signals we can help to make a person aware of his muscle strength level and also give a detailed indication about different diseases to the doctors.

TABLE VII
TIME AND MEMORY CONSUMPTION OF DIFFERENT MODELS FOR DIFFERENT DATASET SPLITS FOR DIFFERENT HAND GESTURES

	Dataset with 80/20 split		Dataset with 70/15/15 split		10-fold CV	
Model	**Time (s)**	**Memory usage (MB)**	**Time (s)**	**Memory usage (MB)**	**Time (s)**	**Memory usage (MB)**
SVM	265.11	118.32	274.32	120.34	256.37	119.71
RF	76.87	0.001	72.41	0.001	**71.65**	**0.001**
DT	81.22	0.001	66.53	0.001	65.89	0.001
ANN	410.33	74.56	371.45	75.23	333.76	76.56

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