MACHINE LEARNING TECHNIQUE USED WITH ELECTROMYOGRAPHIC DATA

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Abstract

Corresponding electromyography data, reports, and reactions. Following that, four machine learning techniques were applied to the data sets: random forest, linear regression, support vector machine, and logistic regression. The random forest approach outperforms the other two in both data sets, according to comparisons of accuracy and recall rates amongst various algorithms. Additionally, comparisons between each algorithm's cases with and without deviation standardisation have been made, and the findings show that the deviation standardisation has a specific impact on the improvement of accuracy. It is also discovered that the random forest algorithm is capable of displaying the ranking of the features in terms of relevance. It has been demonstrated that the random forest method is utilised to diagnose facial paralysis and injury to the ear nerve. To create the best algorithm for computer-aided diagnosis systems, the proposed system uses two datasets consisting 575 facial motor nerve conduction study reports and 233 auditory brainstem reen.

Keywords: Machine learning, electromyography, feature extraction, random forest, support vector machine

I. INTRODUTION

Nerve electrophysiology (EMG), a discipline for examining the bio-electrical activities of nerve and muscle cells, has been used in medicine for almost a century. Since many years ago, a full range of clinical electrophysiological evaluation technologies, such as electromyography, electroencephalography, and evoked potentials, has been established on the basis of nerve electrophysiology. With regard to the qualitative localization, pathological extent, and prognosis of peripheral neuropathy, as well as the differential diagnosis of neurogenic diseases and myogenic diseases, this examination technology is crucial from a clinical standpoint. Machine learning algorithms, including traditional machine learning algorithms, deep learning algorithms, and reinforcement learning algorithms, are a crucial component of artificial intelligence and have been

widely applied in the medical industry to aid in the detection and treatment of diseases. Many efforts have been made in the past few years to apply machine learning to clinical diagnostics. In JAMA magazine in 2016, the Gulshan team from the University of California showed how artificial intelligence could identify diabetic retinopathy from more than 100,000 retinal fundus pictures. The artificial intelligence algorithm outperforms the manual judgement in terms of sensitivity and specificity when compared to 54 ophthalmologists with US doctor licences. There have been a few successful research projects over the years in the area of open literature documenting the use of electromyography (EMG) data by artificial intelligence and machine learning. EMG data were mostly employed in qualitative analysis from the 18th century, when it was invented, through the end of the previous century.

Scope of Problem

For neuro disorders, an early and precise diagnosis is crucial to the patient's full recovery or improved health after treatment. Clinical examinations alone may not always be sufficient for diagnosis. For diagnosis, EMG recordings are more helpful than a clinical examination. The importance of the face in visual communication. One may automatically deduce many nonverbal cues from a person's face, including their identity, intent, and emotional state. Hearing is made possible by the ear. The inability to move the facial muscles on either side is referred to as facial paralysis. A rare form of hearing loss called auditory neuropathy results from ear nerve injury. In order to provide standardised instruments for medical assessment, treatment, and monitoring and to lower healthcare costs through the incorporation of automatic processes, computer-based automatic facial paralysis and ear nerve injury diagnosis is necessary.

II. SYSTEM DESIGN

The overall architecture of the proposed system will first load the tweets from the dataset which is already given. Then, the structure of the analysis is further stated in detail and some design considerations about it are discussed.

Architecture of the Proposed System

The proposed system is basically composed off our main modules.

1. Data Collection and Pre-processing
2. Data Standardization
3. Applying Machine Learning Techniques with and without data standardization
4. Performance comparison and finding the dominant feature.

The first module is data acquisition, which is a process of gathering EMG data and to Diagnosis the facial paralysis or ear nerve damage; the collected data set undergo various steps of preprocessing to make our dataset suitable for the application of machine learning algorithms and subsequent analysis and the second module is normalizing the data.

The third module is applying the machine learning algorithms for normalized and not normalized data. Fourth module is performance comparison of various machine learning algorithms with and with normalization.

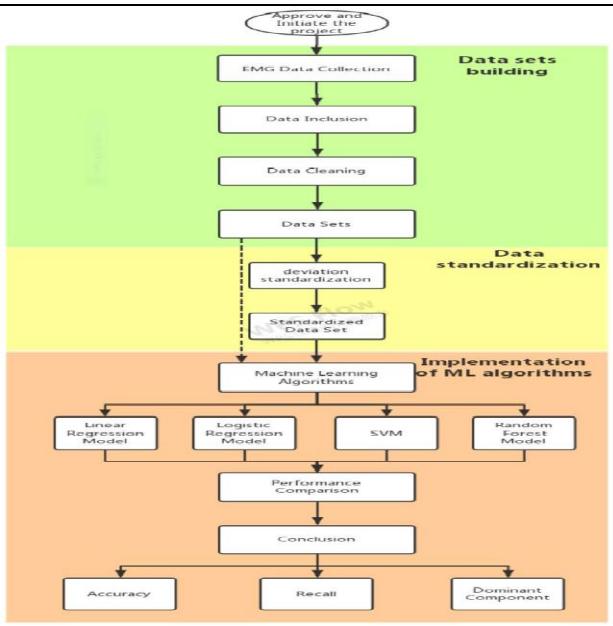

Fig Overall Architecture

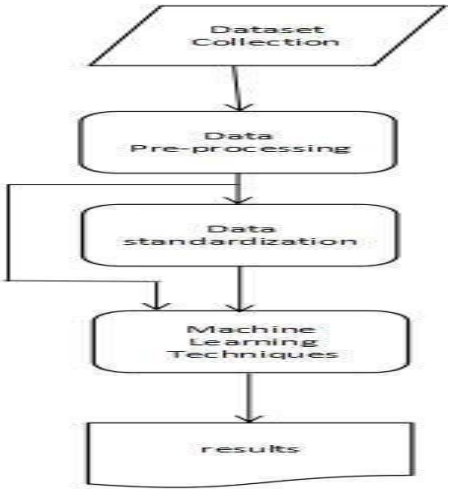

Figure 4.2.1: Workflow of proposed system

III. DATA COLLECTION AND PROCESSING

1. Data Set Collection

Firstly, 2,352 electromyography examination reports have been recorded from Sichuan Provincial Hospital of Traditional Chinese Medicine for ten months. The data cleaning has been conducted based on the specific-designed inclusion criteria. Next, two data sets have been established.

1. 575 facial motor nerve conduction study reports
2. 233 auditory brainstem response reports

FMNCS data set is used for the diagnosis of Facial Paralysis and ABR data set is used for diagnosis of Ear Nerve damage.

2. Data Set Description

Data field	Description
In/Out_Patient	Hospitalization status
Age	Patient's age
Sex	Patient's gender
Date	Date of electromyography
Do_ABR	Whether the ABR check was done meanwhile
Do_Blink	Whether the Blink check was done meanwhile
RT_L_Latency	Left latency of rami temporalis
RT_L_Amplitude	Left amplitude of rami temporalis
RT_L_Area	Left area of rami temporalis
BB_L_Latency	Left latency of buccal branch
BB_L_Area	Left area of buccal branch
BB_L_Amplitude	Left amplitude of buccal branch
RT_R_Latency	Right latency of rami temporalis
RT_R_Amplitude	Right amplitude of rami temporalis
RT_R_Area	Right area of rami temporalis
BB_R_Latency	Right latency of buccal branch
BB_R_Area	Right area of buccal branch
BB_R_Amplitude	Right amplitude of buccal branch
abnormal	inspection result

Table 3.1: Data fields and descriptions for **F-MNCS** examination data

F-MNCS Data

	In/Out_Pa	Age	Sex	Date	RT_L_Late	RT_L_Amp	RT_L_Area	RT_R_Late	RT_R_Amp	RT_R_Area	BB_L_Late	BB_L_Amp	BB_L_Area	BB_R_Late	BB_R_Amp	BB_R_Area	Do_Blink	Do_ABR	abnormal
2	in	33	0	########	3	1.35	1.516	2.96	2.36	2.105	2.82	1.94	4.574	2.66	3.64	9.319	0	0	1
3	in	38	0	########	2.4	1.71	3.643	2.54	0.8	0.1692	2.52	3.86	10.63	2.58	1.57	3.076	1	1	1
4	out	50	0	########	2.5	2.16	2.698	2.62	1.12	2.097	2.8	4.8	11.68	2.84	2.31	5.586	0	1	1
5	out	60	1	########	2.92	2.95	6.696	2.98	1.31	1.673	2.78	4.77	7.647	2.96	2.02	1.39	0	0	1
6	in	45	0	########	2.64	1.8	6.448	2.76	0.31	0.2618	2.5	4.9	9.081	2.84	0.47	0.1829	1	1	1
7	in	68	1	########	2.52	1.48	2.841	2.34	2.69	4.865	2.56	1.38	2.136	2.32	2.54	2.938	0	0	1
8	out	25	0	########	2.92	2.64	2.881	2.64	2.66	5.113	2.76	2.46	2.206	2.54	2.61	5.958	0	0	0
9	in	41	1	########	2.8	2.23	5.182	2.76	1.91	4.812	0	0	0	0	0	0	0	0	0
10	out	30	1	########	2.34	2.6	8.278	2.64	0.93	2.301	2.36	5.08	16.1	2.64	2.26	6.019	0	0	1
11	in	28	0	########	2.48	1.71	1.736	3.16	0.45	0.7687	2.34	1.4	1.082	3.36	0.48	1.94	0	0	1
12	in	72	1	########	2.96	1.81	2.644	2.8	0.29	0.1378	2.56	2.39	4.61	2.72	0.33	0.1815	0	0	1
13	in	42	0	########	2.72	2.05	3.309	3.4	0.42	0.1471	2.68	2.2	1.903	3.36	0.36	0.5308	1	1	1
14	out	52	0	########	2.8	2.38	4.897	3.56	0.5	0.8255	2.74	2.49	3.936	3.72	0.55	1.266	0	0	1
15	out	26	1	########	2.42	2.89	7.375	2.8	0.86	1.212	2.4	2.29	6.264	2.76	0.69	0.6219	0	1	1
16	out	50	0	########	2.76	0.75	1.402	2.4	1.73	2.206	2.66	0.98	3.134	2.36	2.47	5.682	0	0	1
17	in	46	0	########	2	1.91	4.358	3.08	0.34	0.4846	2.2	4.71	13.34	3.24	0.79	0.7508	0	0	1
18	in	25	1	########	2.38	2.21	5.943	2.6	1.02	2.684	2.48	2.96	6.476	2.7	1.28	2.944	0	1	1
19	in	40	1	########	2.3	1.95	6.025	2.92	0.34	1.113	2.48	2.28	5.757	2.96	0.41	0.5582	0	1	1
20	in	38	1	########	2.48	2.32	5.869	2.56	1.19	1.143	2.74	3.28	5.729	2.74	1.52	3.05	0	0	1

Table 3.2: F-MNCS dataset

Data field	Description
In/Out_Patient	Hospitalization status
Age	Patient's age
Sex	Patient's gender
Do_MNCSF	Whether the facial MNCS check was conducted at the same time
Abnormal	Examination result
L_Smit	Left stimulus frequency
R_Smit	Right stimulus frequency
R_Latency_1	Right latency 1
R_Latency_2	Right latency 2
R_Latency_3	Right latency 3
R_Latency_4	Right latency 4
R_Latency_5	Right latency 5
R_Latency_A	Right latency A
R_Latency_B	Right latency B
L_Latency_1	Left latency 1
L_Latency_2	Left latency 2
L_Latency_3	Left latency 3
L_Latency_4	Left latency 4
L_Latency_5	Left latency 5
L_Latency_A	Left latency A
L_Latency_B	Left latency B
R_Interval_13	The interval on the right I–III
R_Interval_35	The interval on the right III–V
R_Interval_15	The interval on the right I–V
R_Amp_5A	The amplitudeon the right V–A
R_Amp_1B	The amplitudeon the right I–B
L_Interval_13	The interval on the left I–III
L_Interval_35	The interval on the left III–V
L_Interval_15	The interval on the left I–V
L_Amp_5A	The amplitudeon the left V–A
L_Amp_1B	The amplitudeon the left I–B

Table 3.3: Data fields and descriptions for **ABR** examination data

ABR Data

	In/Out_Pa	Age	Sex	R_Latency	R_Latency	R_Latency	R_Latency	R_Latency	R_Latency	R_Latency	L_Latency	L_Latency	L_Latency	L_Latency	L_Latency	L_Latency	L_Latency	R_Smit	L_Smit	R_Interval	R_Interval	R_Interval	L_Interval	L_
2	in	69	male	1.67	2.66	3.91	4.75	5.98	6.42	2.42	1.59	2.42	3.71	4.71	5.7	6.06	1.95	95	95	2.24	2.07	4.31	2.12	
3	in	65	male	1.47	2.62	3.85	4.89	5.83	6.54	2.03	1.41	2.58	3.85	4.77	5.8	6.14	1.83	90	90	2.38	1.98	4.36	2.44	
4	out	75	female	1.45	2.66	3.69	4.75	5.58	5.88	1.51	1.63	2.68	3.71	4.75	5.58	5.9	1.81	105	105	2.24	1.89	4.13	2.08	
5	out	29	female	1.2	2.2	3.54	4.6	5.09	6.29	nan	1.28	2.16	3.31	4.38	5.13	5.88	nan	95	95	2.34	1.55	3.89	2.03	
6	in	63	female	1.48	2.4	3.68	4.48	5.48	6.35	nan	nan	nan	3.77	4.98	6.35	6.35	nan	105	105	2.2	1.8	4	nan	
7	out	43	female	1.5	2.45	3.62	4.71	5.7	6.2	1.96	1.54	2.51	3.58	4.77	5.56	6.07	2.04	90	90	2.12	2.08	4.2	2.04	
8	out	70	female	1.45	2.6	3.75	4.69	5.72	6	1.79	1.51	2.66	3.59	4.87	5.56	5.88	1.79	105	105	2.3	1.97	4.27	2.08	
9	out	10	male	1.39	2.33	3.72	4.53	5.45	6.27	nan	1.31	2.31	3.62	4.49	5.33	6.22	nan	90	90	2.33	1.73	4.06	2.31	
10	in	38	female	1.63	2.72	3.67	4.73	5.66	6.02	2.32	1.57	2.58	3.63	4.57	5.56	6.1	2.18	90	90	2.04	1.99	4.03	2.06	
11	out	42	female	1.53	2.56	3.65	4.55	5.66	6.04	1.89	1.51	2.54	3.63	4.71	5.72	6.16	2.01	90	90	2.12	2.01	4.13	2.12	
12	in	78	female	1.53	2.5	3.5	4.43	5.32	5.82	1.13	1.37	2.46	3.38	4.45	5.34	5.82	1.81	105	105	1.97	1.82	3.79	2.01	
13	in	66	male	1.65	2.6	4.03	4.83	6.04	6.59	1.95	1.77	2.56	3.99	4.67	6.08	6.44	1.91	105	105	2.38	2.01	4.39	2.22	
14	in	45	female	1.47	2.62	3.4	4.61	5.32	5.94	1.97	1.45	2.68	3.58	4.54	5.38	5.78	1.97	90	90	1.93	1.92	3.85	2.13	
15	out	44	female	1.51	2.72	3.63	4.65	5.5	6.02	2.01	1.53	2.56	3.58	4.83	5.53	6.03	1.89	90	90	2.12	1.87	3.99	2.05	
16	in	69	male	1.59	2.66	3.63	4.65	5.56	6.1	1.25	1.51	2.82	3.71	4.63	5.58	6.12	1.87	90	90	2.04	1.93	3.97	2.2	
17	out	39	female	1.39	2.56	3.65	4.53	5.46	5.84	1.65	1.35	2.76	3.67	4.53	5.46	5.9	1.61	90	90	2.26	1.81	4.07	2.32	
18	in	70	female	1.87	2.94	4.15	4.96	6	6.44	2.4	1.59	2.7	3.83	4.87	5.84	6.34	2.38	105	100	2.28	1.85	4.13	2.24	
19	in	42	female	1.55	2.72	3.71	4.81	5.64	6.1	2.07	1.99	2.92	4.91	4.81	6.02	6.44	2.5	90	100	2.16	1.93	4.09	2.2	
20	out	75	female	1.45	2.66	3.69	4.75	5.58	5.88	1.51	1.63	2.68	3.71	4.75	5.58	5.9	1.81	105	105	2.24	1.89	4.13	2.08	

Table 3.4: ABR dataset

IV. DATA STANDARDIZATION

The data standardization is the foundation of machine learning. Both dimension and value of an indicator would make a great difference when it comes to evaluating an indicator. Without data processing, the results of the data analysis would be affected. The common standardization methods include decimal calibration standardization, standard deviation standardization and deviation standardization.

Decimal Calibration Standardization

This method is to map attribute values to [−1,1] by shifting decimal numbers of attribute values. This method is mainly used is to eliminate the influence of the units. Its conversion formulacan be described.

$$x * = x/10k$$

Standard Deviation Standardization

The standard deviation standardization is a method which can make the mean and the standard deviation of the data to be 0 and 1, respectively. This standardization method can be appliedto eliminate the effect of units and the variation of variables. Its conversion formula can be expressedas:

$$x^* = (x - \bar{x}) / \sigma$$

where x denotes the original data, $\bar{x}$ represents the mean, and σ is the standard deviation.

Deviation Standardization

The deviation standardization is a method of linear mapping the original data to [0,1]. Its main purpose is to remove the impact of dimensions and range of the data, while maintaining the linear relationship among the original data. The specific definition can be written as follows:

$$x * = (x - \min) (\max - \min)$$

where max denotes the maximum of the sample data, min represents the minimum of the sample data.

Machine Learning Techniques

In this study, we use a machine learning approach. Different types of machine learning techniques are used for diagnosis of facial paralysis and ear nerve damage. Machine learning techniques train the algorithm with some specific training data with known outputs, thereby allowing working with new test data. Several machine learning algorithms include Linear Regression, Logistic Regression, Support Vector Machine (SVM), and Random Forest (RF) used to build the study machine learning classifier.

- **Support Vector Machine**

Support vector machine a set of supervised learning methods supports detection of classification, regression, and outliers that are helpful for statistical theory of learning. However, primarily, it is used for Classification problems in Machine Learning. The goal of the SVM algorithmis to create the best line or decision boundary that can segregate n-dimensional space into classes sothat we can easily put the new data point in the correct category in the future. This best decision boundary is called a hyper plane. SVM chooses the extreme points/vectors that help in creating the hyper plane. These extreme

cases are called as support vectors, and hence algorithm is termed as Support Vector Machine.

- **Random Forest (RF)**

Random Forest (RF) is a technique of classification and regression based on the ensemble method, which is based on the bagging of bootstraps. Boosting and bagging are the two commonly known and used techniques for the classification of trees. The random forest consists of a combination of trees that can be used to predict the class label based on the categorical dependent variable for a specified data point. Using a random subset of the original features, each decision tree is trained. Inthis paper, the CART algorithm is used as the decision tree algorithm for the construction of the randomforest.

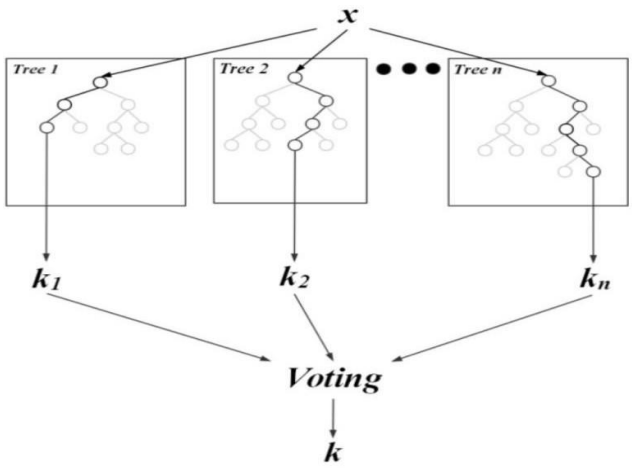

Fig 3.1: Schematic of random forest for CART algorithm.

- **Linear Regression**

Linear regression is one of the easiest and most popular Machine Learning algorithms. It is a statistical method that is used for predictive analysis Linear regression algorithm shows a linear relationship between a dependent (y) and one or more independent (y) variables, hence called as linear regression. Since linear regression shows the linear relationship, which means it finds how the value of the dependent variable is changing according to the value of the independent variable. The linear regression model provides a sloped straight line representing the relationship between the variables. Consider the below image:

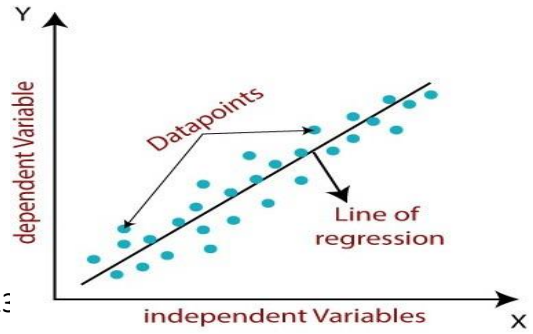

Fig.3.2: Schematic of Linear Regression model

- **Logistic Regression**

Logistic regression is used for predicting the categorical dependent variable using a given set of independent variables. It is a supervised learning algorithm. Logistic regression predicts the output of a categorical dependent variable. Therefore the outcome must be a categorical or discrete value. It can be either Yes or No, 0 or 1, true or False, etc. But instead of giving the exact value as 0 and 1, it gives the probabilistic values which lie between 0 and 1.

V. RESULTS

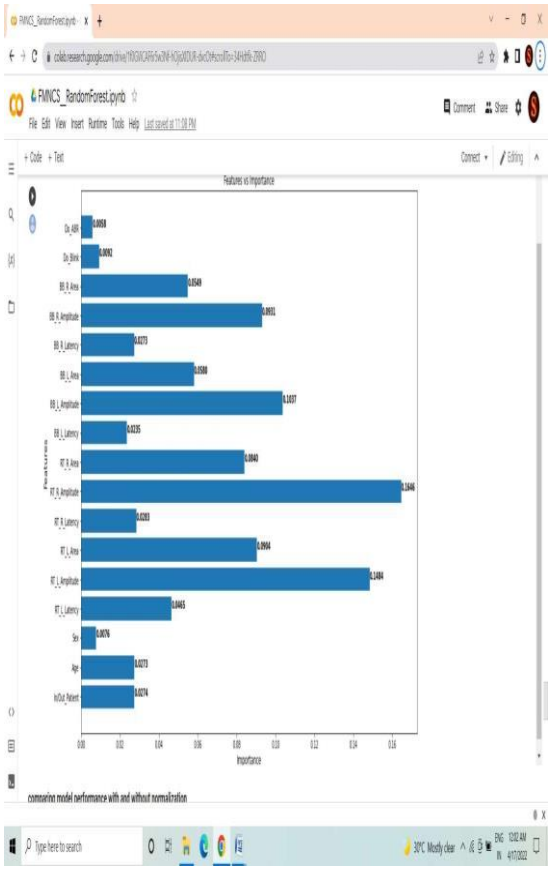

Fig 5.1: Feature Importance Graph for RF classifier

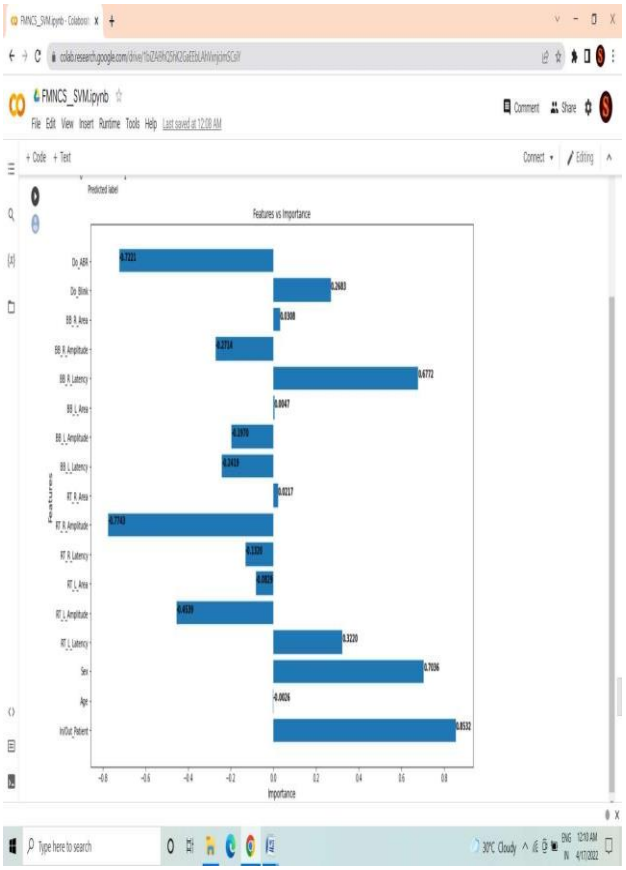

Figure 5.2: Feature Importance Graph for SVM

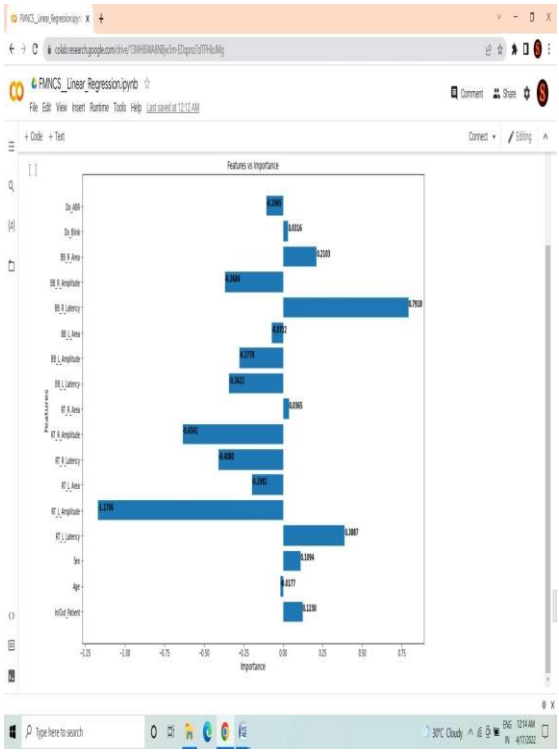

Fig.5.3: Feature Importance graph of Linear Regression Classifier

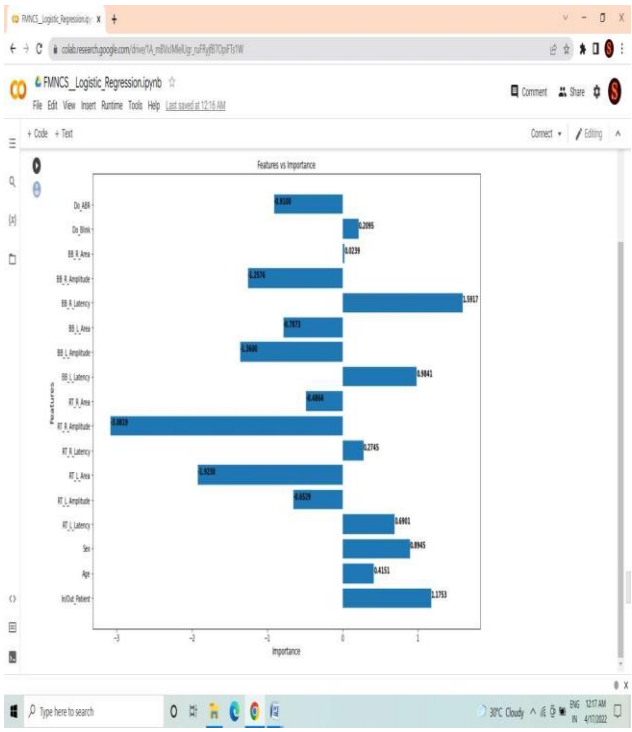

Fig 5.4: Feature Importance graph

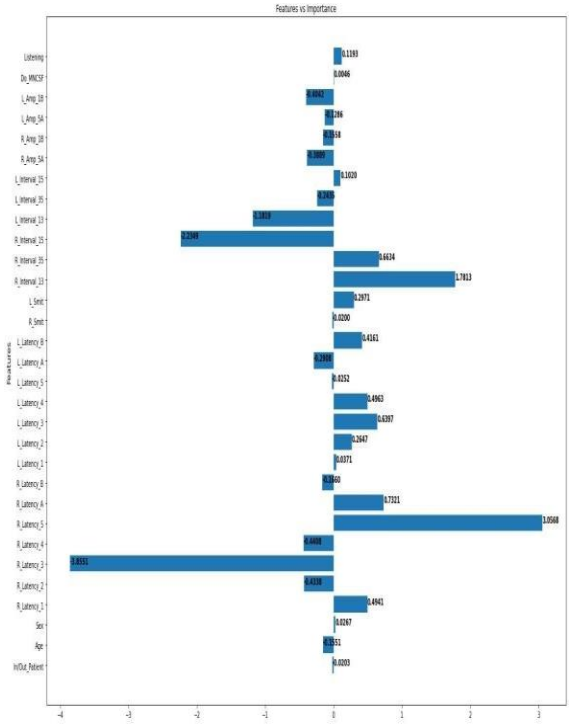

Fig 5.5: Feature importance graph

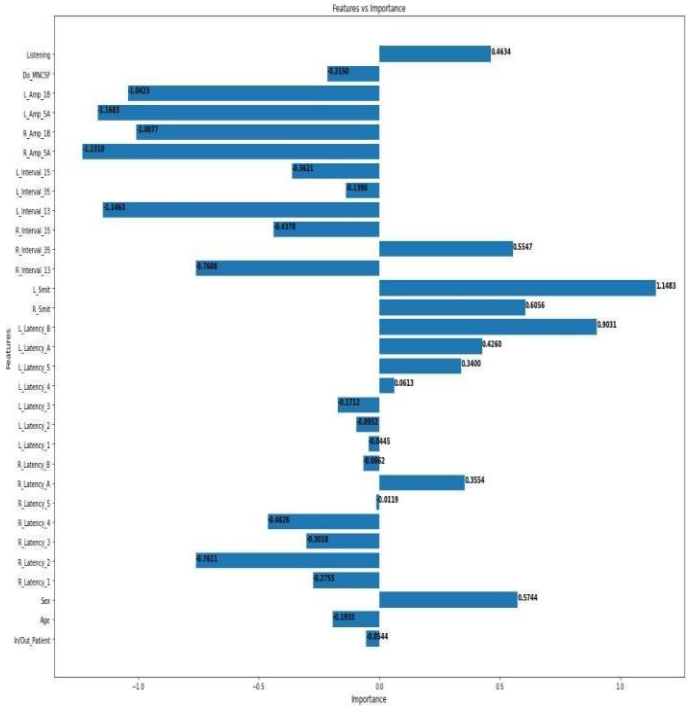

Fig 5.6: Feature importance graph for logistic regression for ABR data

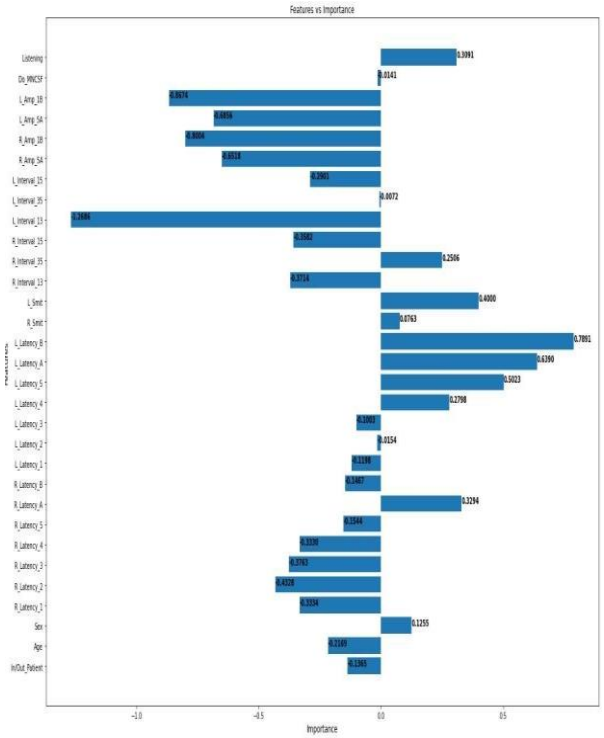

Fig 5.7: Feature importance graph of SVM for ABR data

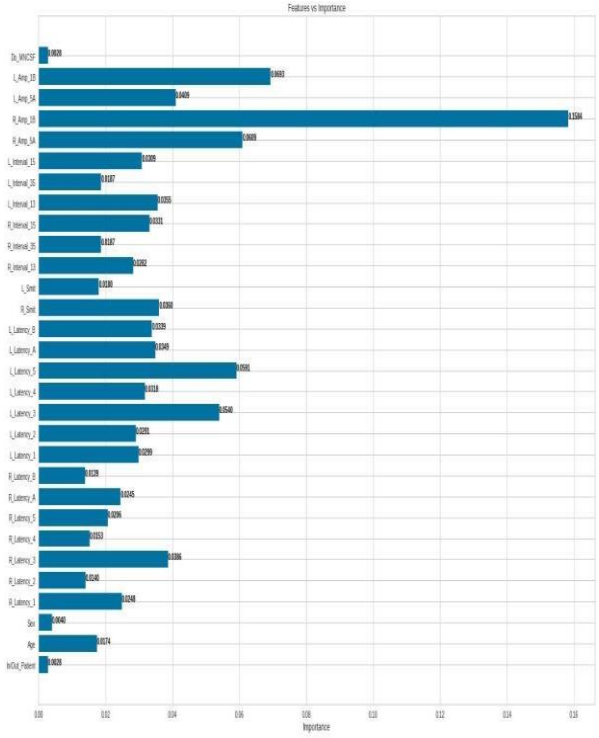

Fig 5.8: Feature Importance graph for Random Forest for ABR data

ANALYSIS OF RESULTS

Model performance comparisons of F-MNCS data with normalization

	random forest	Logistic Regression	Linear Regression	svm
Accuracy	0.9443	0.8695	0.8695	0.8660
Recall	0.9874	0.9832	0.9706	0.9475
Precision	0.9482	0.8756	0.8840	0.8969

Table 5.1: Model performance comparisons of F-MNCS data with normalization

Model performance comparisons of F-MNCS data with out normalization

	random forest	Logistic Regression	Linear Regression	svm
Accuracy	0.9336	0.8660	0.8513	0.8567
Recall	0.9843	0.9495	0.9539	0.9368
Precision	0.9396	0.8741	0.8533	0.8641

Table 5.2: Model performance comparisons of F-MNCS data without normalization

Model performance comparisons of ABR data with normalization

	random forest	Logistic Regression	Linear Regression	svm
Accuracy	0.9009	0.8927	0.8625	0.8882
Recall	0.5	0.45	0.4823	0.4
Precision	0.8216	0.8466	0.8613	0.875

Table 5.3: Model performance comparisons of ABR data with normalization.

Model performance comparisons of ABR data without normalization

	random forest	Logistic Regression	Linear Regression	svm
Accuracy	0.8967	0.8840	0.8625	0.8757
Recall	0.475	0.4	0.4823	0.375
Precision	0.8216	0.8416	0.8613	0.7666

Table 5.4: Model performance comparisons of ABR data without normalization

VI. CONCLUSION

Based on performance evaluations of four machine learning algorithms, it can be concluded that the random forest method performs better in EMG data, particularly in F-MNCS and ABR data, than the linear algorithm and logistic algorithm. Additionally, data standardisation, such as derivation standardisation, is a successful technique for enhancing performance, such as accuracy. Meanwhile, it is discovered that BB_L_Latency, followed by BB_R_Latency, is the most important influencing factor of the F-MNCS test. While the remainder of the inspection indicators have little impact on the outcomes, RT_R_Latence and RT_L_Latence also have some degree of influence. Regarding the ABR examination, L_Latency_5, L_Latency_A, and L_Interval_35 have the greatest impacts, followed by L_Latency_b and L_Latency_4.

VII. FUTURE WORK

The project's future research will focus on detecting EMG data based on the waveform of the data and calculating the results of various tests based on the waveform's properties. Currently, the doctor performs this procedure manually based on the waveform's properties. A comprehensive system can be developed when the approach used in this work and other research are combined. The ultimate objective is to expedite the EMG test in order to utilise all available medical resources.

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