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A Gestation Diabetic Detection Technique using Muscle Energy Derived from Surface EMG

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Abstract- Electromyogram (EMG) is one among the important biopotential signal reflecting the human skeletal muscle activity. EMG signals can be used for many biomedical applications pertaining to diagnosis and therapy of musculoskeletal and rheumatological problems. EMG signals are complex in nature and require advanced techniques for analysis, such as decomposition, detection, processing, and classification. Diabetes mellitus is a chronic metabolic disorder characterized by elevated levels of blood glucose. The musculoskeletal system can be affected by diabetes in a number of ways. The main aim of the paper is to identify the diabetic patient and show the classification performance of the proposed framework. In this paper EMG signal is investigated by feature extraction and are classified into normal and diabetic for comprehension of EMG signal. The primary point of this work is to recognize the diabetes utilizing different elements and to demonstrate the performance of the proposed framework. The obtained results demonstrate that the extracted feature in proposed framework displays better performance for classification the EMG signal contrasted with alternate elements. Based on the impacts of features on the EMG signal classification, different results were obtained through analysis of the SVM Classification. Experimental study shows that the proposed method's classification accuracy is 98.98%.

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AGESTATIONDIABETICDETECTIONTECHNIQUEUSINGMUSCLEENERGYDERIVEDFROMSURFACEEMG

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Anjaneya L. H α, Mallikarjun S. Holi σ & Dr. S. Chandrasekhar ρ

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I. Introduction

For the evaluation and administration of patient health, observing of physiological and physical signal is crucial. Electromyogram is a critical health pointer. EMG is likewise utilized as a part of numerous sorts of exploration labs, incorporating those included in engine control, neuromuscular physiology, biomechanics, development issue, postural control, and exercise based recuperation. Physiological and anatomical properties of muscles are presented by the signals; an EMG sign is the electrical action of a muscle's engine units, which comprise of two sorts: surface EMG, and intramuscular EMG [1]. Surface EMG and intramuscular EMG signs are recorded by non-intrusive cathodes and obtrusive terminals, separately. Nowadays, surface-identified signs are ideally used to acquire data about the time or power of shallow muscle enactment [2].

Electromyography (EMG) signs are viewed as most valuable as electrophysiological signs in both medical and engineering fields. The essential strategy for comprehension the human body's practices under typical and neurotic conditions is given by the recording of EMG signs. At whatever point an EMG sign is being recorded from the muscle, different sorts of clamors defile it. In this way, dissecting and characterizing the EMG signs is exceptionally troublesome on account of the complicated pattern of the EMG, particularly when EMG movement happens. EMG is controlled by sensory system and relies on upon anatomical and mental properties of muscles. It is an electrical sign gained from diverse organs. EMG is typically an element of time, discussed in terms of amplitude, phase and frequency. Electromyography (EMG) signs presents to the electrical movement of a muscle amid compression [1].

These signs may be recognized from skin surface anodes or from needles set specifically inside of the muscle. These two sorts of recordings are utilized for diverse purposes, with needle recording used to recognize the conduct of individual muscle motor and fiber units while surface recordings are utilized to distinguish general muscle action specifically positions or activities. Surface EMG is not a typical clinical technique; however it might be utilized as a part of restoration (rehabilitation). Needle electromyography is utilized to figure out if there is harm to nerve filaments to individual muscles. At the point when nerve sends the sign to start muscle constriction a potential is produced over the muscle because of the stream of particles all through muscle cells (i.e. developments of electrolytes) and this ionic current is changed over into electronic current with Ag-AgCl anodes put on the surface of the skin of the contracting muscle. Recently a surface electromyography is progressively utilized for recording from shallow muscles in clinical conventions, where intramuscular cathodes are utilized for profound muscle only [3].

The innovation of EMG is moderately new. There are still restrictions in characterization and detection of EMG sign, phase estimation, procuring suitable data because of induction from typicality. Conventional framework remaking calculations have different impediments and extensive computational complexity quality and numerous show high differences.

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Recently in innovations of signal handling and numerical models have made it to create progressed EMG location and examination strategies [4]. In this way, look into and broad researches have been made in the zone, growing better algorithms, overhauling existing approaches, enhancing recognition methods to diminish clamor, and to gain exact EMG signals. It is very imperative to do an examination to group the real issues of EMG signs investigation and legitimize the acknowledged measures. Higher-order factual routines may be utilized for analyzing the EMG signal because of the one of a kind properties of measurable techniques connected to arbitrary time arrangement. This paper identifies with the redesigning existing procedures filtering, processing, decomposition and modeling of EMG. In our proposed work our principle expect to recognize and order the diabetic patient for that EMG signal information has been considered to do the work. By utilizing the EMG signal it can be dissected what nerves have been harmed and how broad that harm is. An electromyography (EMG) test is often done in conjunction with a Nerve Conduction Velocity (NCV) test. It shows how well muscles are receiving signals from the nerves. Damaged nerves won't send clear or consistent messages.

Reminder of this paper is organized as follows: Section 2 presents the related work in this area. Section 3 presents proposed method for classifying EMG diabetic signal. Section 4 gives detailed description about the result obtained. And the paper is concluded in Section 5.

II. Related Work

This section provides the previous researches in the field of EMG signal processing i.e. feature extraction, noise removal, filtering and classification.

Nishikawa and Kuribayashi et al. [1], Used neural system to segregate hand movements for EMG-Controlled Prostheses. Here the neural system was utilized to take in the connection between EMG signal's energy spectrum and the movement errand craved by the incapacitated subjects.

Xiao Hu; Qun Yu et al. [2] presented a novel and basic technique to extricate the general element of two surface EMG sign examples: lower arm supination surface EMG flag and lower arm pronation surface EMG signal. The system decays surface EMG signal into 16 Frequency groups (FB) by wavelet bundle change (WPT), and afterward wavelet coefficient entropy (WCE) of two picked FBs is ascertained. The two WCEs were utilized to recognize FS surface EMG signals from lower arm supination surface EMG signals. The outcome demonstrates that WCE is a powerful technique for removing the component from surface EMG signal.

kouchaki, s.; Boostani et al. [3] proposed a compelling combinational feature to upgrade the accuracy of classification among the control group and subjects with neuropathy and myopathy illnesses. All EMG signs were create and simulated artificially, by fusing measurable and morphological properties of every group into their sign models, in the EMG lab of Waterloo University. To characterize the subjects by the proposed system, in the first place, EMG signs are deteriorated by observational mode decay or Empirical mode decomposition(EMD) to its regular subspaces, then number of subspaces is adjusted through every windowed sign, and Kolmogorov Complexity (KC) and other informative component are resolved to uncover the measure of anomaly inside of every subspace. Finally, these elements are connected to support vector machine (SVM).

ZhaojieJu; Gaoxiang Ouyang et al. [4] proposed and assessed systems for nonlinear feature extraction and nonlinear classification to recognize distinctive hand controls taking into account surface electromyography (sEMG) signals. The nonlinear measures are accomplished in light of the repeat plot to represent to dynamical attributes of sEMG amid hand movements. Fuzzy Gaussian Mixture Models $(FGMMs)$ are proposed and utilized as a nonlinear classifier to perceive distinctive hand handles and close by controls caught from diverse subjects. Different trials are led to assess their execution by looking at 14 individual elements, 19 multifeatures and 4 distinct classifiers. The test results exhibit the proposed nonlinear measures give vital supplemental data and they are key to the great execution in multifeatures.

Artug, N.T.; Goker et al. [5] proposed another system for feature extraction. In this study another dataset are prepared for neuromuscular sicknesses utilizing checking EMG strategy and four new components are extricated. These components are described as duration of phase, maximum amplitude the maximum amplitude, and maximum amplitude times phase duration, and number of peaks. By utilizing factual values, for example, mean and variance, number of elements has expanded up to eight. This dataset was characterized by utilizingk-nearest neighbors calculation $(k-NN)$, radial basis function networks (RBF), support vector machines (SVM), andmulti-layer perceptron (MLP).

III. Proposed System

As a result of the different clamors and antiques identified among EMG signs, obliged data remains an amalgam inside the raw EMG signals. Then again, if these raw signals are utilized as a data as a part of sEMG order, the proficiency of the classifier reduces. To enhance the performance of the classifier, researchers have been utilizing distinctive sorts of EMG elements as an information to the classifier. To accomplish ideal order execution, the properties of EMG highlight space should be taken into consideration. There are three sorts of EMG components in diverse spaces: time area, frequency area and time-frequency space features. Hudgins et al. created time area elements of the sEMG. They utilized mean absolute value (MAV), mean absolute value slope, slope sign changes (SSC), waveform lengths (WL) and zero crossing (ZC) for presenting to myoelectric examples. These components are termed as 'the Hudgins highlight'. A deliberately chose set of info components gives a higher grouping rate than the crude sign. In the journey to enhance, the precision of myoelectric sign example grouping Englehart et al. looked at time space (TD) components utilized by Hudgins with the time recurrence area highlights (TFD). Time-recurrence area elements are viable capabilities particularly for transient myoelectric sign example characterization. Because of the high dimensionality and high-determination issue of time-frequency representation, dimensionality lessening is regularly an important supplement to highlight extraction. Every one of them should be possible progressively and electronically and it is straightforward for usage. Feature in this group are regularly utilized for onset identification, muscle constriction and muscle action recognition.

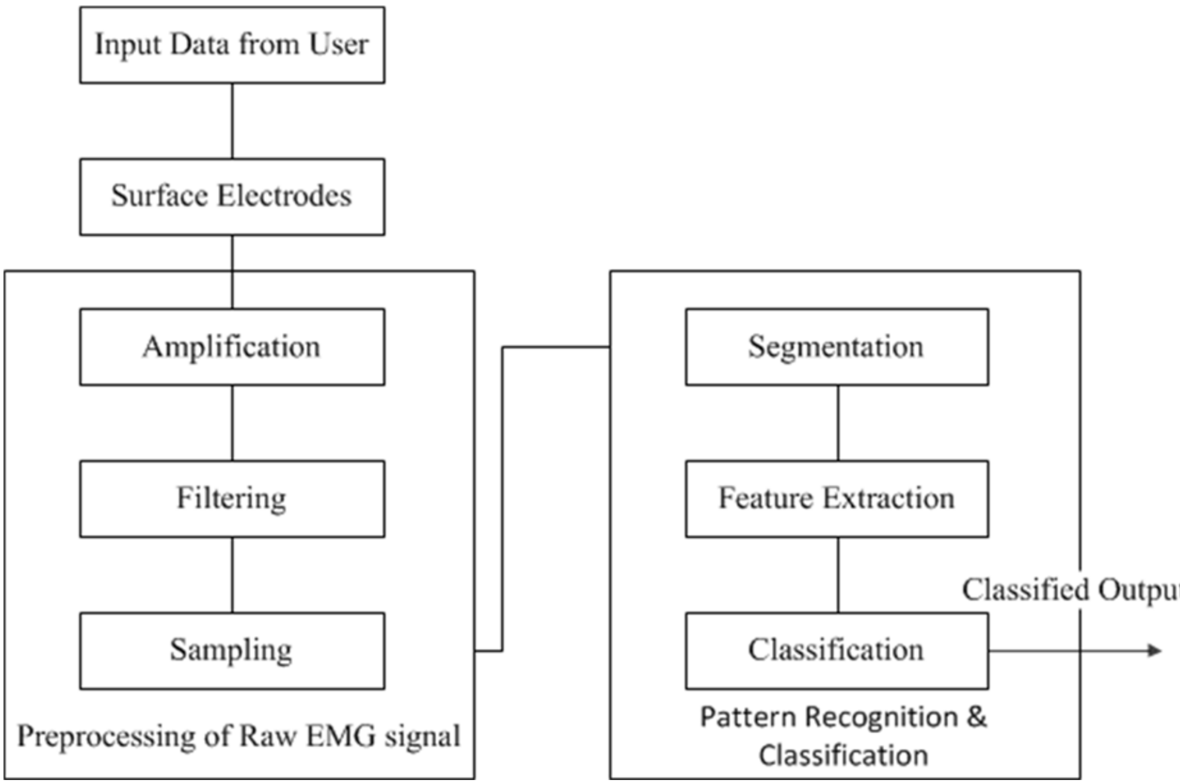

Figure 1 : Overall System Architecture

Above given fig1 presents the overall architecture of the framework. To collect the EMG data surface electrodes are being used, this data is called raw data. To perform the desired operation on this data we need to do some preprocessing on this data i.e. amplification, filtering and sampling. The next step is to perform segmentation on the data. After this step the data is divided into samples which are compatible for feature extraction. In our proposed framework various features are extracted which are described below.

Fifteen time domain features and frequency domain features are described in this section. Thirteen time domain variables are measured as a function of time. Because of their computational simplicity, time domain features or linear techniques are the most popular in EMG pattern recognition. Integrated EMG, Mean absolute value, Modified mean absolute value 1, Modified mean absolute value 2, Mean absolute value slope, Willison amplitude Zero crossing, Root mean square, Slope sign change, Variance of EMG, Waveform length and Histogram of EMG are used to test the performance. Additionally, highlights in recurrence area are utilized to speak to the identify muscle weakness and neural anomalies, and at some point are utilized as a part of EMG example acknowledgment. Three customary and two adjusted elements in recurrence range are performed specifically autoregressive coefficients, mean and middle frequencies, changed mean and middle frequencies. A while later, the assessment techniques for two models that used to quantify the power property of the entire components are presented. Finally the classification is done on the feature extracted data.

IV. Feature Extraction in Time Domain

a) Integrated EMG

Integrated EMG ($IEMG$) is computed as the summation of the total estimations of the $sEMG$ signal amplitude. For the most part, $IEMG$ is utilized as an onset list to recognize the muscle movement that used to approaching the control charge of assistive control gadget. It is identified with the $sEMG$ sign arrangement terminating point, which can be communicated as

$$IEMG = \sum_{n=1}^{N} |x_n|, \tag{1}$$

where N denotes the length of the signal and x_n represents the $sEMG$ signal in a segment.

b) Mean Absolute Value

Mean Absolute Value (MAV) is like normal corrected quality. It can be figured utilizing the moving normal of full-wave amended EMG. It is ascertained by taking the normal of the total estimation of $sEMG$ sign. It is a simple route for location of muscle compression levels and it is a prominent element utilized as a part of myoelectric control application. It is characterized as

$$MAV = \frac{1}{N}\sum_{N=1}^{N} |x_n| \tag{2}$$

c) Modified Mean Absolute Value 1

It is an addition in MAV using weighting window functionw_n. It can be defined as

$$MAV1 = \frac{1}{N}\sum_{n=1}^{N} w_n|x_n| \tag{3}$$

$$w_n = f(x) = \begin{cases} 1, if\ 0.25N \le n \le 0.75N \\ 0.5 \quad\quad\quad\quad ,otherwise \end{cases}$$

d) Modified Mean Absolute Value 2

Modified Mean Absolute Value 2 ($MMAV2$) is similar to $MMAV1$. In this method by using continuous weighting window functionw_n , the smooth window is improved. It is given by

$$MMAV2 = \frac{1}{N}\sum_{n=1}^{N} w_n|x_n| \tag{4}$$

$$w_n = \begin{cases} 1, if\ 0.25N \le n \le 0.75N \\ \dfrac{4n}{N}, if\ 0.25N > n \\ \dfrac{4(n-N)}{N}, if\ 0.75 < n. \end{cases}$$

e) Mean Absolute Value Slope

Mean Absolute Value Slope ($MAVSLP$) is a modified version of MAV. The differences between the $MAVs$ of adjacent segments are determined. It can be defined as

$$MAVSLP_i = MAV_{i+1} - MAV_i \tag{5}$$

f) Variance of EMG

Variance of EMG (VAR) uses the power of the $sEMG$ signal as a feature. Generally, the variance is the mean value of the square of the deviation of that variable. However, mean of EMG signal is close to zero. In consequence, variance of EMG can be calculated by

$$VAR = \frac{1}{N-1}\sum_{n=1}^{N} x_n^2 \tag{6}$$

g) Root Mean Square

Root Mean Square (RMS) is modeled as amplitude modulated Gaussian random process whose RMS is related to the constant force and non-fatiguing contraction. It relates to standard deviation, which can be expressed as

$$RMS = \sqrt{\frac{1}{N}\sum_{n=1}^{N} x_n^2} \tag{7}$$

h) Waveform Length

It is a measurement of cumulative length of the waveform over time segment. $WL$is related to the waveform amplitude, frequency and time. It is given by

$$WL = \sum_{n=1}^{N-1} |x_{n+1} - x_n| \tag{8}$$

All of these features above, eq.1-eq.8 are computed based on sEMG signal amplitude. From the experimental results, the pattern of these features is similar. Hence, we selected the robust feature representing for the other features in this group. The results and discussion is presented in Section 4.

i) Zero Crossing

Zero intersection (ZC) is the quantity of times that the adequacy estimation of sEMG sign crosses the zero y-axis. In EMG highlight, the edge condition is utilized to go without the background clamor. This component gives a surmised estimation of recurrence space properties. It can be detailed as

$$ZC = \sum_{n=1}^{N-1} [\, sgn(x_n \times x_{n+1}) \cap |x_n - x_{n+1}| \geq threshold] \tag{10}$$

$$sgn(x) \begin{cases} 1, & if\ x \geq threshold \\ 0, & otherwise \end{cases}$$

j) Slope Sign Change

Slope Sign Change (SSC) is like ZC. It is another technique to present to the recurrence data of sEMG sign. The quantity of changes in the middle of positive and negative slant among three continuous portions is performed with the edge capacity for keeping away from the impedance in sEMG signal. The count is characterized as

$$SSC = \sum_{n=2}^{N-1} [f[(x_n - x_{n-1}) \times (x_n - x_{n+1})]]; \tag{11}$$

$$f(x) = f(x) = \begin{cases} -1, & if\ x \geq threshold \\ 0 & ,\ otherwise \end{cases}$$

k) Willison Amplitude

Willison amplitude (WAMP) is the quantity of times that the contrast between sEMG signal adequacy among two contiguous portions that surpasses a predefined limit to lessen commotion impacts same as ZC and SSC. The definition is as

$$WAMP = \sum_{n=1}^{N-1} f(|x_n - x_{n+1}|); \tag{12}$$

$$f(x) = \begin{cases} 1, & if\ x \geq threshold \\ x & ,\ otherwise \end{cases}$$

WAMP is related to the firing of motor unit action potentials (MUAP) and the muscle contraction level. The suitable value of threshold parameter of features in ZC, SSC, and WAMP is normally chosen between 10and 100 mV that is dependent on the setting of gain value of instrument. Nevertheless, the optimal threshold that suitable for robustness in sEMG signal analysis is evaluated and discussed in Section 4.

V. Frequency Domain Feature Extraction

a) Autoregressive Coefficients

Autoregressive (AR) model described each sample of sEMG signal as a linear combination of previous samples plus a white noise error term. AR coefficients are used as features in EMG pattern recognition. The model is basically of the following form:

$$x_n = -\sum_{i=1}^{p} a_i x_{n-i} + w_n, \tag{13}$$

where x_n is a sample of the model signal,w_n is AR coefficients,w_n is white noise or error sequence, and p is the order of AR model. The forth order AR was suggested from the previous research [19]. However, the orders of AR between the first order and the tenth order are found. The results are discussed in Section 4.

b) Modified Median Frequency

Modified Median Frequency (MMDF) is the frequency at which the spectrum is divided into two regions with equal amplitude. It can be expressed as

$$\sum_{j=1}^{MMDF} A_j = \sum_{j=MMDF}^{M} A_j = \frac{1}{2}\sum_{j=1}^{M} A_j, \tag{14}$$

where A_j is the sEMG amplitude spectrum at frequencybin j.

c) Modified Mean Frequency

Modified Mean Frequency (MMNF) is the average frequency. MMNF is calculated as the sum of the product of the amplitude spectrum and the frequency, divided by the total sum of spectrum intensity, as in

$$MMNF = \sum_{j=1}^{M} \frac{f_j A_j}{\sum_{j=1}^{M} A_j}, \tag{15}$$

where f_j is the frequency of spectrum at frequency bin j.

According to the proposed method for EMG classification the above given mathematical equation are used for the frequency and time domain feature extraction.

Because of the way of the EMG signal, there would be an extensive variety in the estimation of specific features between individuals. Numerous elements, for example, changes in terminal position, sign preparing will deliver changes in highlight values after some time. A suitable acknowledgment technique must have the capacity to oblige the normal individual contrast. SVM Classifier hypothesis assumes an imperative critical part in managing vulnerability when settling on choices in biomedical field of uses. The classifier proposed for the grouping of the EMG signs was executed by a basic methodology in view of Support Vector Machine is to arrange the EMG sign to one of the classifications, Diabetic or Non-Diabetic.

VI. Results and Discussion

a) Data Recording Stage

The EMG records correspond to the activity of the uterine muscles and might therefore be used to predict the premature onset of labor. Records were collected from the general population as well as from the patients admitted to the hospital with the diagnosis of impending pre-term labor. One record pre-pregnancy was recorded. The records are of 30-minduration and consist of three channels. The sampling frequency, fs, was 20 Hz. The records were collected from the abdominal surface using four AgCl2 electrodes. The electrodes were placed in two horizontal rows, symmetrically under and above the navel, spaced7 cm apart. A special protocol was used during the attachment of the electrodes in order to improve the quality of the measurements [13]. According to the protocol, the resistance between the electrodes had to be lower than $100\ k\Omega$. The first acquired signal was measuredbetween the topmost electrodes (E2–E1), the second signal between the leftmost electrodes (E2–E3) and the third signal between the lower electrodes (E4–E3). Prior to sampling the signals were filtered using an analog three pole Butterworth filter with the bandwidth from 0 to 5 Hz. The resolution of the scanning system was 16 bits with the amplitude range ±2.5 mV.

In our experiment we have considered 297 users EMG signal data. Out of 297, 295users are not having diabetes and the remaining 2 users are diabetic affected.

The given table 1 shows the mean and standard deviation for all the features for diabetic patient.

Table 1 : Mean and standard deviation measurement of all the features

FEATURES	MEAN	STD
Integrated EMG	-59.609	503.9653
Mean Absolute Value	246.3694	132.842
Modified Mean Absolute Value 1	187.0663	102.1839
Modified Mean Absolute Value 2	124.7915	69.9963
Mean Absolute Value Slope	-3.313	36.7025
Variance of EMG	5.24E+06	7.33E+06
Root Mean Square	0.01	0.0059
Waveform Length	3.77E+04	2.08E+04
Zero Crossing	32.125	9.4582
Slope Sign Change	58.1528	6.9995
Willison Amplitude	97.4556	0.7376
Autoregressive Coefficients	2.58E+07	3.64E+07
Modified Median Frequency	1.68E+03	1.01E+03
Modified Mean Frequency	486.8818	11.2808

The given table 2 shows the mean and standard deviation for all the features for diabetic patient.

FEATURES	MEAN	STD
Integrated EMG	288.6233	852.8137
Mean Absolute Value	439.7441	237.7973
Modified Mean Absolute Value 1	333.7233	180.5012
Modified Mean Absolute Value 2	221.8945	119.6891
Mean Absolute Value Slope	-1.441	75.8474
Variance of EMG	1.65E+07	1.83E+07
Root Mean Square	0.00116	0.0081
Waveform Length	6.97E+04	3.72E+04
Zero Crossing	31.767	13.7266
Slope Sign Change	5.94E+01	7.83E+00
Willison Amplitude	97.196	0.945
Autoregressive Coefficients	8.11E+07	8.92E+07
Modified Median Frequency	3.07E+03	1.62E+03
Modified Mean Frequency	4.81E+02	1.08E+01

VII. Feature Extraction Stage

In this section the feature extraction and classification steps and their outcomes are presented

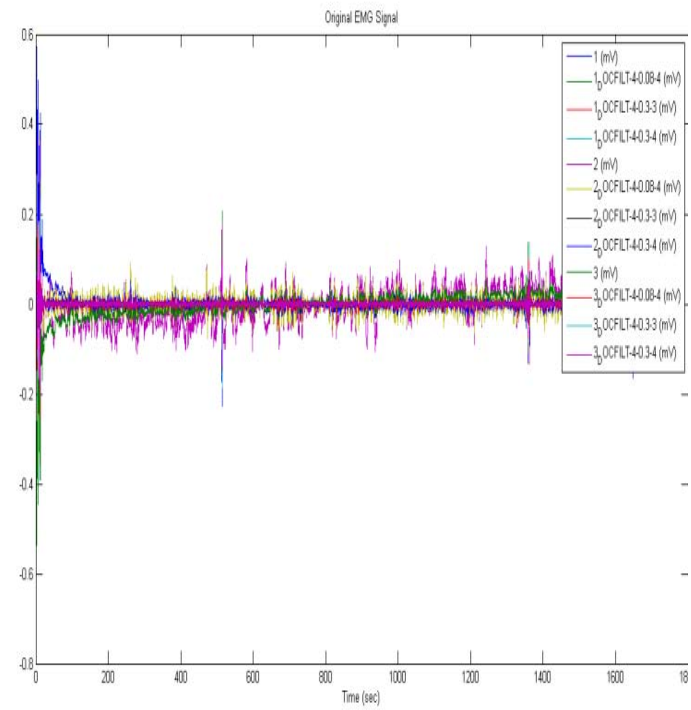

Fig.2 (a) Original Signal

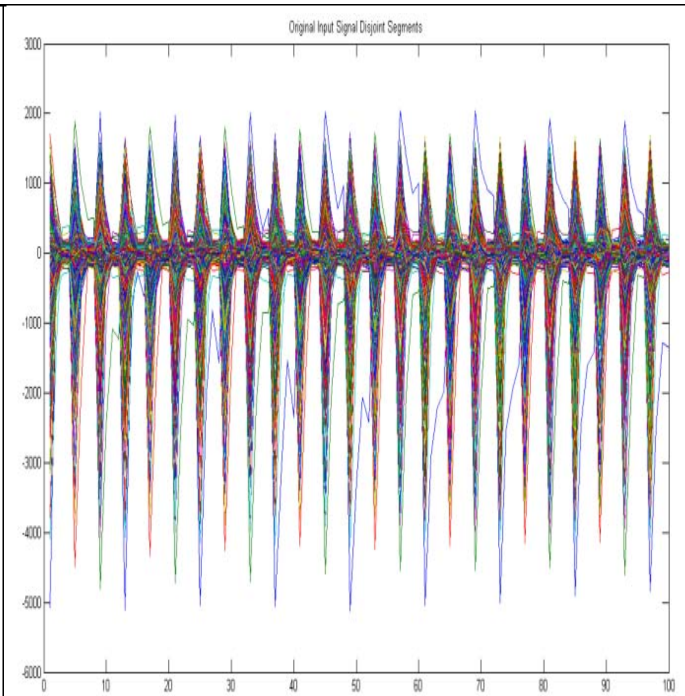

Fig.2 (b) Segmented Signal

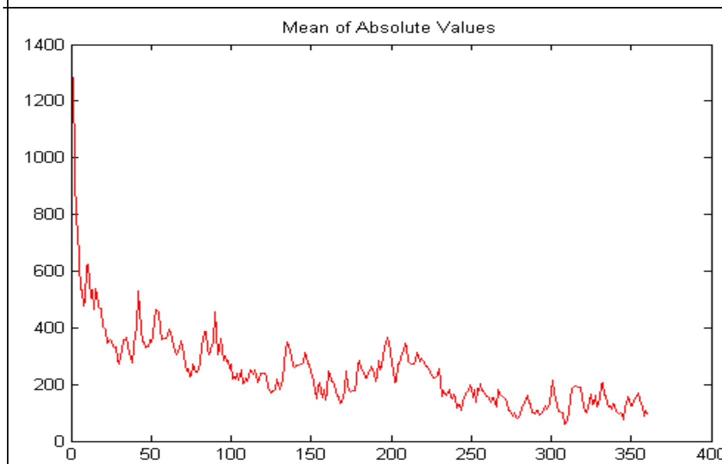

Fig 2. (c) Mean Absolute Value

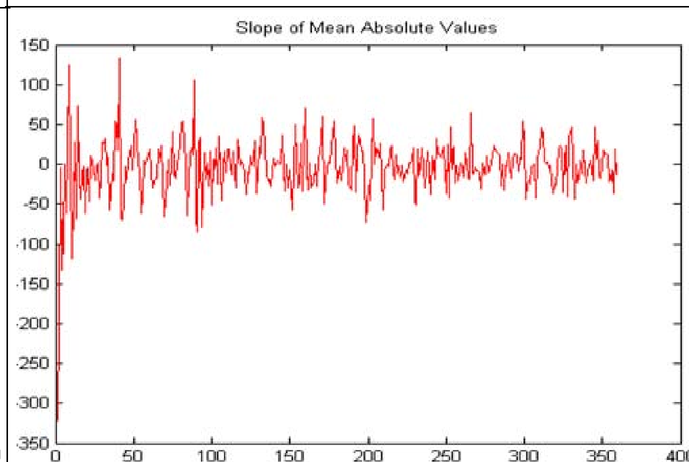

Fig.2 (d) Slope of Mean Absolute Value

Figure 2 : Segmentation & Mean calculation of Raw EMG Signal

The given figure 2 shows the EMG signal processing and feature extraction using our proposed method. Fig 2(a) is the raw signal taken from the electrodes. Fig 2(b) is the segmentation of the raw signal in samples. Fig 2(c) presents the Mean absolute value. In fig 2(d) Slope of Mean Absolute Value.

The next step is to combine all the features in to one matrix for the classification. In our method for non-diabetic user we have assigned class as 0 and for diabetic user class 1 has been assigned. The extracted features combined into one matrix and passed to the SVM classifier for the training the data. After finishing the training step, data is parsed to the prediction stage to get the classification results.

Finally, confusion matrix of classification, precision and recall, specificity and sensitivity of the proposed system are calculated.

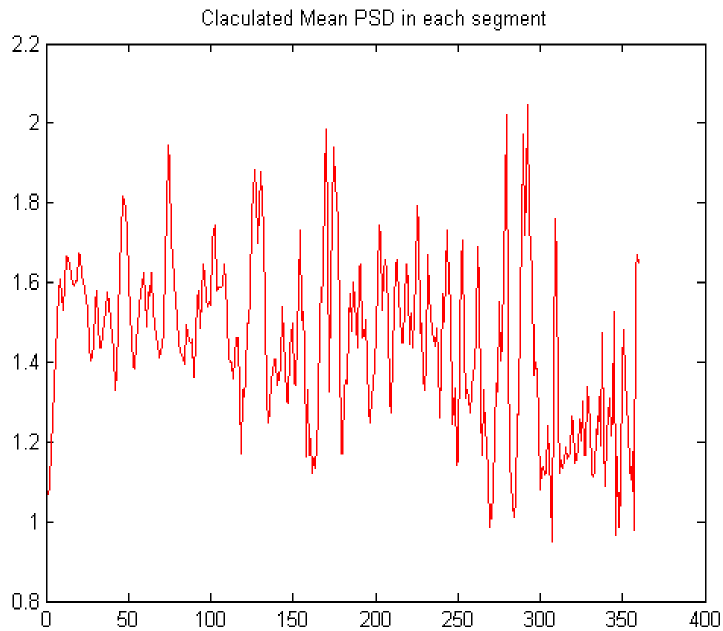

Fig 3 (a) Mean Power spectral density

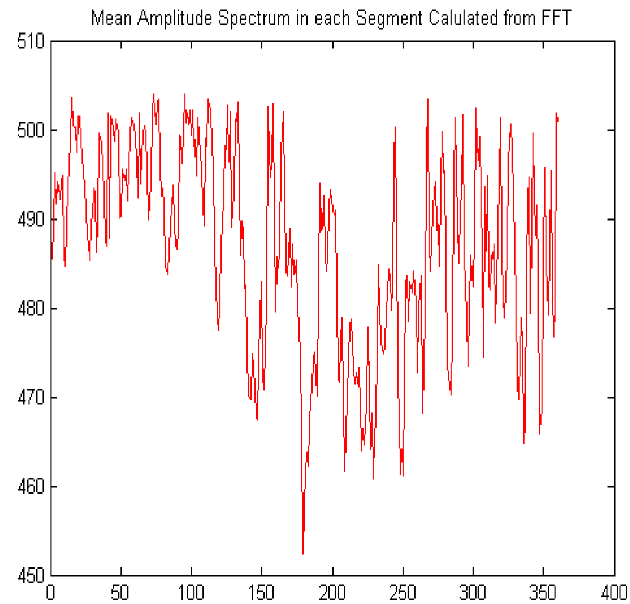

Fig 3 (b) Mean Amplitude Spectrum

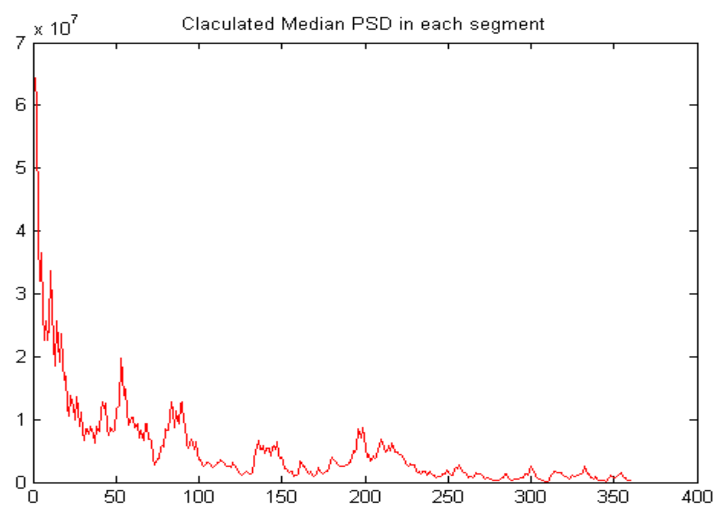

Fig 3(c) Median Power Spectral Density

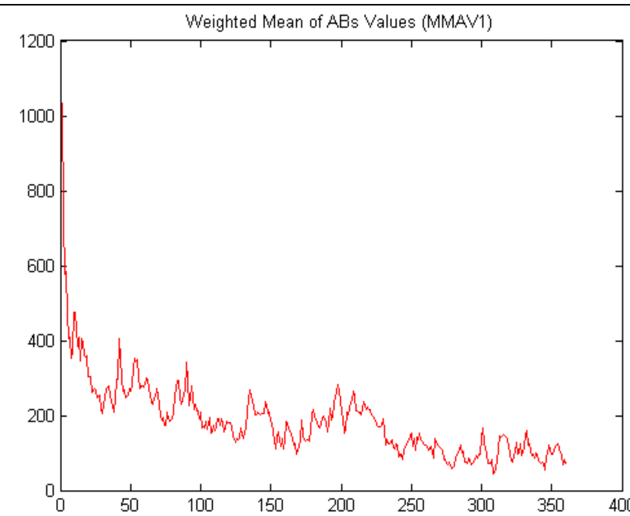

Fig 3(d) MMAV1

Figure 3 : Power Spectral Density and Weighted Mean calculation

The given figure 3 shows the EMG signal Power Spectral Density and Weighted Mean calculation. Fig 3(a) is the mean of power spectral density. Fig 3(b) is the amplitude of mean which is calculated from FFT. Fig 3(c) presents the power spectral density of the median data of the Raw EMG. In fig 3(d) presents the weighted mean of absolute values which is denoted by MMAV1.

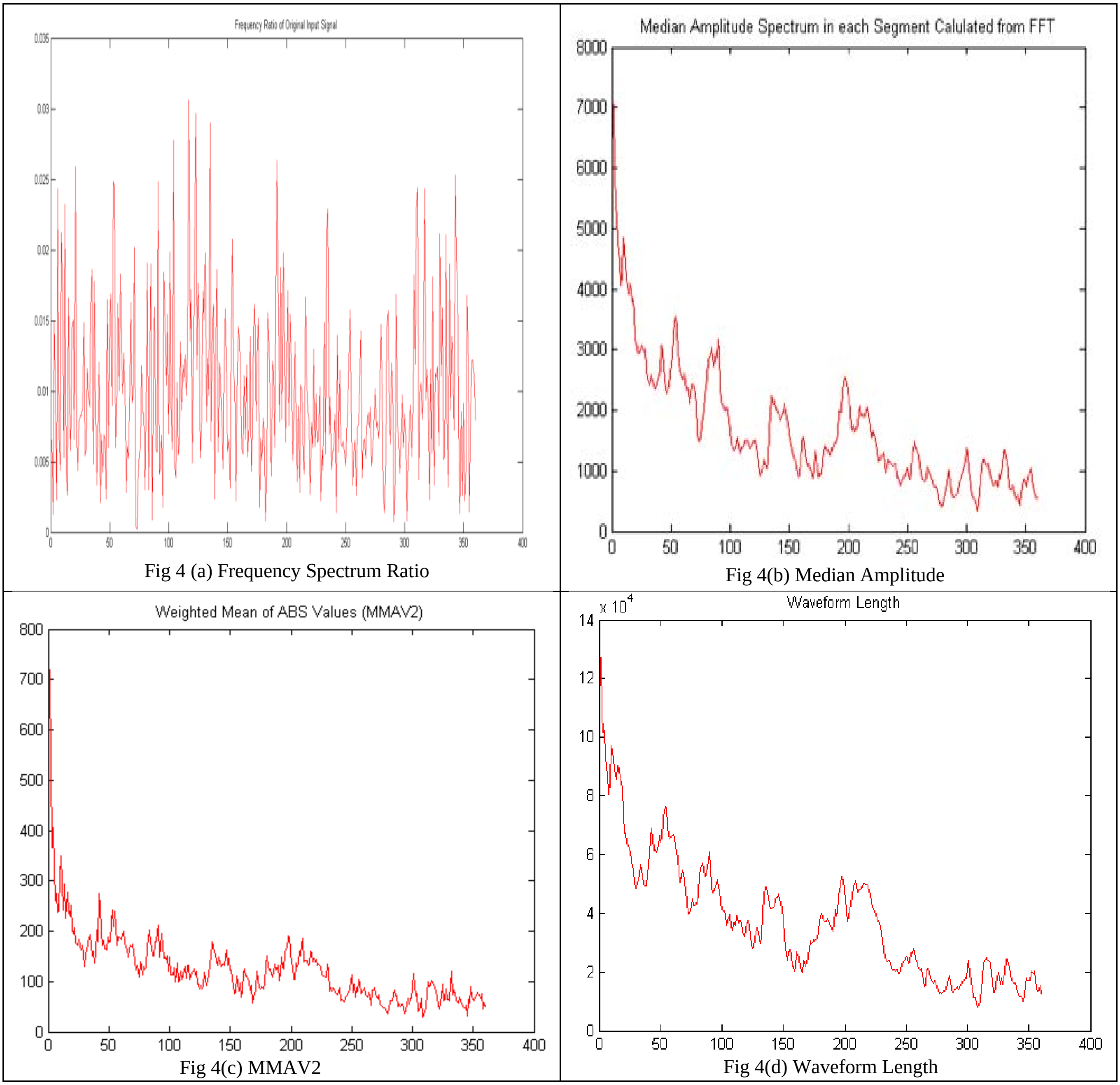

Fig 4 (a) Frequency Spectrum Ratio

Fig 4(b) Median Amplitude

Fig 4(c) MMAV2

Fig 4(d) Waveform Length

Figure 4 : Frequency Spectrum, median amplitude, mean absolute value and Waveform length calculation

The given figure 4 shows the EMG signal Frequency Spectrum, median amplitude, mean absolute value and Waveform length calculation. Fig 4(a) is the frequency ratio of the Raw EMG. Fig 4(b) is the amplitude of median which is calculated from FFT. In fig 4(c) presents the weighted mean of absolute values which is denoted by MMAV2. Fig 4(d) is the waveform length.

VIII. Classification Stage

This is the final stage of our framework in order to achieve the classification results. In this stage all the extracted feature are given to the SVM Classifier. The first step in the classification stage is to train the dataset based on the features extracted from our feature extraction method. After training the dataset one trained model is created based on the feature. This model contains labels of the dataset, indexes and support vectors.

After creating this process of training; this model is given to the SVM prediction step for the classification of the test dataset. In the prediction model the predicted labels are achieved according to the test and train data. Finally the statistics of SVM Classifier is calculated.

Table 1 : Confusion Matrix

292	3
0	2

The above given table represents the confusion matrix of the classifier. According to our dataset we have 297 user's EMG signals. Out of 297, 2 user are having diabetes and remaining are non-diabetes, as we discussed earlier section that for non-diabetes, the class is assigned as 0 and diabetes is 1. It is clear from the confusion matrix that the proposed system is able to identify the diabetes class. It is showing that 292 users are non-diabetic and 2 users are diabetic patient, the remaining 3 users are the misclassification of the approach.

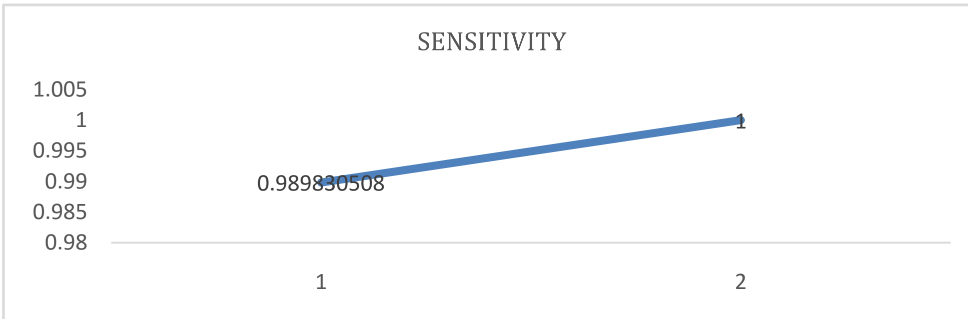

Figure 5 : Sensitivity of the proposed system

In figure 5 another result analysis parameter is plotted which is the Sensitivity of the system. According to this framework, this approach is highly sensitive for the diabetic and non-diabetic class. The x-axis represents the number of class and y-axis represents the sensitivity of the classifier w.r.t the class.

Table 2 : Confusion matrix statistics

RECALL	PRECISION	SPECIFICITY
0.9898	1	1
1	0.4	0.9898

The above given table represents the recall, precision, specificity of the proposed frame work.

$$Precision = TP / (TP + FP)$$

$$Recall = TP / (TP + FN)$$

- Sensitivity (also called the true positive rate, or the recall in some fields) measures the proportion of positives that are correctly identified.
- Specificity (also called the true negative rate) measures the proportion of negatives that are correctly identified.

According to this the precision and recall is calculated for this method.

Total number of users in the dataset is 297 and correctly classified are 294, so the final classification result in terms of accuracy is 98.98%.

IX. Conclusion

The study described the use of the electromyography pattern recognition method, which is very important in different applications, such as rehabilitation devices, prosthetic arm/leg control, assistive technology, symptom detection for neuromuscular disorder, and so on.

In case of a disease monitoring system (i.e. diabetes), two major criteria are applicable—one is robustness and reliability, and another is accuracy of detection. Based on these criteria, the SVM classifier was trained using the extracted features. The experimental results show that the proposed approach is able to classify the diabetes with a better accuracy of 98.9899%.

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