A Deep Learning Classification Approach using Feature Fusion Model for Heart Disease Diagnosis

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Abstract—**Early Diagnosis has a very critical role in medical data processing and automated system. In medical diagnosis, automation is focused in different area of applications, in which heart disease diagnosis is a prominent domain. An early detection of heart disease can save many lives or criticality issues in diagnosing patients. In the process of heart disease diagnosis spatial and frequency domain features are used in making decision by the automation system. The processing features are observed to time variant or invariant in nature and the criticality of the observing feature varies with the diagnosis need. Wherein, the current automation system utilizes the features extracted in a large count to attain a higher accuracy, the processing overhead, and delay are considerable. Different regression approaches were developed in recent past to minimize the processing feature overhead the features are optimized based on gain performance or distance factors. The characteristic variation of feature and the significance of the feature vector are not addressed. This paper outlines a method of feature selection for heart disease diagnosis, based on weighted method of feature vector in consideration of feature significance and probability of estimate. A new optimizing function for feature selection is proposed as a dual function of probability factor and feature weight value. Simulation results illustrate the improvement of accuracy and speed of computation using proposed method compared to other existing methods.**

Keywords—Deep learning approach; heart disease diagnosis; feature fusion model; ECG analysis; weighted clustering; F-Score

I. Introduction

The real time world is tending towards automation with the emergence of new technologies. To improve the system performance, different technologies were proposed to attain higher performance in the process of technologies in automation. The medical data processing is an emerging area of automation. In processing the medical data in making decision, the diagnosis systems were developed based on the captured samples which were passed to the processing unit using advanced processing algorithms. In the processing of medical data for automation, heart disease diagnosis has evolved as an area of interest in recent past. Various approaches have evolved in recent time in diagnosis of an early prediction of heart disease using electrocardiogram (ECG) or physiological parameters defined in Cleveland data set. Cardiac activity is measured as a rapid variation in the process of heart which is based on the physical or mental working condition of a person. ECG signals are measured for the variation of electrical impulses in the heart operation based on the contraction or expansion of heart functioning. This is one of the most dominantly used observations in the diagnosis of heart disease. The process of ECG signal processing requires a high precision of storage and computation to provide an exact prediction of the heart condition. ECG processing has been now observed as a most common observation of various heart disease diagnosing such as arterial fibrillation, post-operative complication in cardio surgery [1,2], etc. The post diagnosis complications and delay in diagnosis results in longer hospitalization leading to critical illness and increases a high cost of treatments as well [3]. High risk of heart disease is observed in older age persons [4], however in recent time a rapid increase in the cases of aged between 40 and 50 is also observed. Different diagnoses of heart disease use ECG signal were presented in literature. R-peak detection for ECG analysis is outlined in [5] square double difference method for the QRS segment localization was outlined. This process is developed for feature extraction from ECG using three steps of operations. Process of sorting, thresholding and approximation of the relative region is presented. The R-peak detection is developed based on the magnitude difference of the RR peak values. The external inference has however limited the decision performance. In [6] a feature extraction process with signal denoising is presented. This method proposed soft thresholding approach in processing of ECG signal. Wavelet based method is used in the extraction of feature vectors and processed for signal denoising. The spectral decomposed bands are processed using soft threshold. The selection of feature vector is improved using K-nearest neighbor (KNN) approach outlined in [7]. This approach developed a classifier model using KNN approach in categorizing QRS patterns in ECG signal analysis. This approach applied a band pass filter in selection of feature vector and noise filtration process. In [8] band pass FIR filter was used in extracting the feature vectors. Totally six features were extracted for QRS pattern using a sliding window approach. An approach of signal denoising using modified Weibull distribution for ECG is presented in [9]. This is a blind method defined for the extraction of signal from the source using independent component analysis. In deriving line patterns Hilbert transformation were used. The extraction of feature vector was processed with normalized multi derivative wavelet used for detection and denoising. The classification of the extraction feature is developed using Euclidian distance where a Nyman Pearson classification is developed in [10]. In [11] a wavelet-based transformation is developed for feature extraction and a temporal relation is used in the developing the feature selection. A feature extraction and selection approach are outlined in [12] where P, T peaks were used in diagnosis of heart disease. The presented approach develops a multi classification for heart disease diagnosis. A geometrical feature extraction is outlined in [13]. These approaches extract the feature based on the structural representation of ECG signal. The structural variations were derived using 1-D discrete wavelet transformation. The extracted features are however biased with noise effects which lead to misclassification. In classification model, various classifier such as support vector machine (SVM), probabilistic neural network (PNN) and multi-layer perceptron (MLP) back propagated network is outlined in [14, 15, 25]. Artificial intelligence (AI) methods have been used in the diagnosis and early alarming of cardiovascular diseases. The usage of AI in the diagnosis of cardiology application is outlined in [16,17]. These approaches significantly eliminate the baseline wandering and using the linear mapping the classification is performed. In [18] a new classifier model based on kernel driven classifier is presented. The authors in [19, 20] outlines the application of artificial neural network (ANN) and SVM model in classification. Similarly, a cross wavelet transform (XWT) is outlined in [21], where two distinct signals are correlated in deriving the correlation. Other method such as wavelet entropy [22, 23] and signature descriptors [24] were presented in automation of heart diseases diagnosis. In [28, 29] different deep learning techniques based on MRI sample processing for early detection of brain tumors and gliomas is presented. However, the feature overhead, accuracy of feature selection and a proper relation of trained features is constraint. In developing a new feature representation for heart disease diagnosis, a new approach of feature fusion using the property of discrete monitored data with the continuous ECG signals features. The overhead of feature representation is addressed ad significant feature vectors were selected in processing the system faster and more accurate. The contribution to the presented work is listed as:

1) Developed a new feature fusion approach using regression and weighted clustering.

2) Developed a classifier model using deep neural network model using feature selected.

3) Integrated electronic record data with ECG feature vector.

The rest of this paper is outlined in seven sections. Characteristic of the features for a heart disease diagnosis is presented in Section II. Section III outlines the existing approach of feature representation and the proposed approach is outlined in Section IV. Section V present the simulation result obtained for developed work. Section VI outlines the conclusion for the developed work.

II. Feature Representation in Heart Disease Diagnosis

The diagnoses of heart diseases are affected by multiple factors. There are multiple observations which are inter-relative in nature. A proposed selection others feature can improve the estimation performance as well, the accuracy of estimation. The two dominant features used in the diagnosis of the heart disease are the discrete monitoring vector and the continuous varying ECG signal. The observation of the discrete feature vector is presented with 14 dominant feature representations. These features are listed as:

1) Age: Patients age in year.

2) Sex: represent the patient is Male/female gender.

3) Chest pain (CP): define type of chest pain in a patient.

a) Patient having a past record of chest pain referred as typical angina (angina).

b) The patient past record is not effective however current observation of chest pain termed as atypical angina (abnang).

c) Patient with short period chest pain with painful condition termed as non-anginal pain (notang).

d) Patient with illness but with low possibility of heart disease termed as Asymptomatic (asympt).

4) Trestbps: Resting blood pressure of a patient at initial monitoring.

5) Chol: patient's density of cholesterol in mg/dl.

6) Fbs: it is a Boolean representation reflecting the fast state of blood sugar with higher value of 120mg/dl.

7) Restecg: Reflect patient ECG on rest state. This is reflected in 3 states having normal, abnormal or hypertrophy.

8) Thalach: this represents the patient maximum value of heart rate obtained.

9) Exang: this is s Boolean value which indicates the angina pain when exercise.

10) Oldpeak: value of ST variation when rested from exercise.

11) Slope: indicates the variation in the slope when in exercise.

12) Ca: indicate major vessels numbers.

13) Thal: indicate the status of heart condition which could be reversible or non-reversible condition.

14) Num: indicate the class attributes which indicate patient health condition which varies from 0-4 value.

These UCI features are readily available at (https://archive.ics.uci.edu/ml/datasets/Heart+Disease) Cleveland database, which describe the measured discrete coefficient of automation system. A feature selection approach of the monitoring feature of Cleveland data set is presented in our past work [27]. In addition to the measured discrete parameter, a continuous signal monitoring of ECG is used for representation. ECG reads the impulse of heart muscle variations. This reflects the functionality of the heart and the rhythmic repetition indicates the variation of heart movements. A typical ECG signal is measured for a continuous monitoring which could extend from 24-48 hours. For a detail monitor about 12 different observations can be used with different placed sensors. The ECG signals are recorded for a 125Hz to 500 Hz sampling rate which are buffered in 8–12bit binary representation. The volume of discrete samples buffered into a file for processing could range from few Kb's to a large Mb. The interference during the capturing of ECG or buffering is an additional overhead to the buffered data. Basically a ECG signal is captured a 0.05-100Hz frequency range for a value of 1-10mV. ECG signal is characterized by five peaks and valleys which are termed as P, Q, R, S, and T representing the variation of heart movement. The estimation of ECG features defining the PQRST time period, peak values etc. the variation of a P-R interval could extend for 0.2 to 0.2 seconds for a normal heart condition. The duration of the ECG peaks and the amplitude variations in QRST representation diagnosis different heart disease cases such as cardiac arrhythmias, ventricular hypertrophy, myocardial infection, Arterial fibrillation etc. A representation of an ECG is signal is presented in "Fig. 1".

The ECG signal is characterized by the varying coordinates of the signal and the 12 features used in the process of diagnosis are as listed:

1) R_pk_cnt – Number of R peaks in the signal
2) Q_Dur – Q time period
3) R_Dur – Period of R-R time interval
4) R_Ampl – Amplitude for R peak
5) Q_Ampl - Amplitude for Q peak
6) S_Ampl - Amplitude for R peak
7) P_Loc – location of P
8) Q_Loc - location of Q
9) R_Loc - location of R
10) S_Loc - location of S
11) T_Loc - location of T
12) ST_dev- ST deviation

The variations of these parameters reflect the variation in heart movement which is used in the diagnosis of heart disease. The automation system developed in diagnosis of heart disease read these features as an input parameter in making decisions and diagnosis of different heart disease. In recent [26] a fusion model for ECG feature and medical record data is presented. The feature fusion model is developed based on the cluster information gain for a normalized factor. The presented approach of feature fusion is presented in following section.

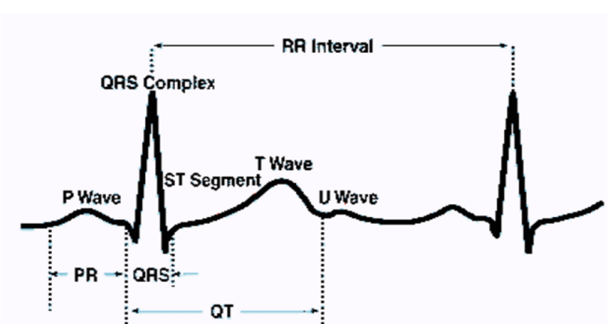

Fig. 1. Figure Illustrate ECG Signal Representation with Feature Representation. different Segment of ECG Shown in Figure P Wave, PR Interval, QRS, ST Segment and T Wave [25].

III. Embedded Feature Fusion Approach

The representing features for diagnosis are very important in representing the variations in observing data. Features for heart disease diagnosis are observed by recording sensor interface or by recording physical or medical history of a patient. As multiple sources of feature vector exist developing different processing and classification system is very complex and overhead for automation system. Fusion of multiple observations can reduce the overhead in automation process. Fusion can be developed based on data, feature or decision level. A feature based fusion approach is proposed in [26]. This approach attempts to fuse the patient record data with the sensor monitoring features. The framework for feature fusion approach proposed in [22] shown in "Fig. 2". An integration of physiological data observed via sensors with the electronic recorded data is developed.

The data recorded are preprocessed for its representation and improve the quality of representation. A signal denoising, missing data filtering and normalization. The presented approach developed a feature fusion selection method based on information gain and entropy of information. Here, a set of feature vectors are structured obtained from sensors and record data. The feature selection is optimized by observing the information gain factor (IGF). IGF of the feature vector is represented as,

$$IGF\ (f, f') = \ \nu(f) - \nu(f, f') \tag{1}$$

Where f, f' are the feature vectors of sensor and recorded data, respectively. $\nu(.)$ is the entropy function of the variable. The entropy (ν) of a feature set is measured based on the redundancy parameters of the feature vectors in a class given by,

$$\nu(f_i) = \ -\sum_{i=1}^{k} P(f_i) log_2\big(P(f_i)\big) \tag{2}$$

Where $P(.)$ is the probability factor for a feature entering into cluster. The selection of the feature vector is governed by the distance metric of the entropy value of the two observing feature vectors. An optimization is observed when the distance is minimal. The information gain is then defined by,

$$IGF\ (f, f') = \ -\sum_{i=1}^{k} P(f_i) log_2\big(P(f_i)\big) - \big(-\sum_{i=1}^{k} P(f_i) - \sum_{i=1}^{k} P(f_i)\ log_2\big(P(f_i, f_i')\big)\big) \tag{3}$$

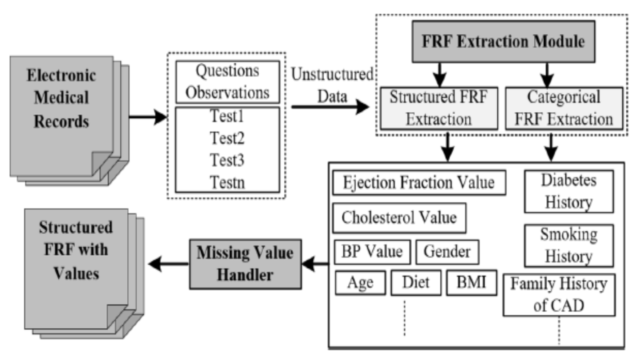

Fig. 2. Work Flow for Feature Fusion and Decision for Heart Disease Analysis. Figure Illustrate the Extraction of Features from Unstructured Electronic Medical Record.[26].

The presented work discards the features with low information gain and select only features with high information gains. The selection is based on the higher values of IGF which is relative to the entropy of a feature value. The presented work discards the features based on the redundancy of the feature vector in the set. A weight-based feature selection is also presented in prioritization of feature selection. However, the outline work though improves estimation accuracy discard the features with reference to redundancy factor. The process of low entropy feature elimination reduces the processing overhead but, the criticality of the feature set is not observed. Secondly, the redundancy wrt. Vector magnitude is observed but the diversity in feature vector in fusion is not considered. This discard features of importance due to similar magnitude values. To overcome the addressed issue, a new regression model with divergence factor is presented. The outlined method is presented in the following section.

IV. Weighted Feature Fusion Model and Classification

Feature fusion based on entropy eliminates features of low magnitude or higher redundancy; however, the significance of such features was not observed with the criticality of heart disease. Elimination of feature of higher critical features having higher entropy could lead to lower estimation performance and hence should be selected based on feature criticality. An approach based on the divergence of feature vector and its importance based on its criticality called weighted feature fusion model (WFM) is presented. The proposed feature selection is developed based on an auto regressive model. The auto regression approach has a significant means of selecting appropriate fusion of record data with ECG features simultaneously. The auto regression method is developed based on the information theory approach where the optimization is achieved using burg's method. The method minimizes the information loss based on feature vectors and the approximation of test feature with the registering group (Gi). For a given set of feature vector$\{f, f'\}$, where f is the features derived from the grouping of ECG signal$(f_{ECG})$and the record values(f_R) of patient physiological details and f' is the feature set of other classes.

$$f = \{f_{ECG}, f_R\} \tag{4}$$

An auto regression for the feature set is computed to derive the variation (γi) using distance metric for all 'j' features set in the group given as,

$$\gamma_i = (f_i - f'_{i,j})^2 \tag{5}$$

To observe the criticality of the feature vector a weight value is associated with different class of heart disease based on the severity factor. Severity of the heart disease is defined in 5 different classes as listed in Table I, where each class group is associated with a weight value indicating its criticality. The weight value of each class is allotted based on its criticality. Here a higher value of 0.5 is given to class-4 type of heart disease and 0.1 is given to the healthy class. The associated weight value for each class is presented in Table I.

TABLE I. Weight Association with Class Attribute from Electronic Record Data. The Weight Value of each Class is Allotted based on its Criticality

Group (G_i)	**Class**	**Infection level in %**	**Categorize**	**Weight allotted (ω_i)**
G_0	Healthy	Nil	Healthy	0.1
G_1	class -1	0-20%	starting level	0.2
G_2	class -2	20-40%	Effective with-Low	0.3
G_3	class -3	40-60%	Effective with – High	0.4
G_4	class -4	60-max%	Significant level	0.5

A regression model is developed for the selection of fusion feature where a Bergman divergence approach is applied for selecting the best suitable feature values. The optimization of feature selection is defined as a minimization function given as,

$$Arg\ min(P[\gamma_i(f, f')]) \tag{6}$$

Features with minimum probability of diversity are eliminated and features with higher diversity are considered for selection. The two-feature set f and $f^{\sim}$ are processed for computing diversity (γi) based on squared distance. The Probability function $P(.)$ defines the probability of diversity among the set of fusion features. The diversity factor is computed as,

$$\gamma_i(f, f') = (f - f')^2 \tag{7}$$

The features with higher diversity factor have a higher probability of selection. However, the proposed approach measures the criticality of the feature in selection based on the class of severity. For the measure of class severity, a weight value is associated listed in Table I.

The features are processed for computing an aggregated weight factor $(A\omega)$ for all k-classes given by,

$$A\omega = \sum_{i=1}^{k} \omega_i \tag{8}$$

Where, ω_i are the associated weight values for each class value. An aggregated class weight (ω_{kc}) for each group (c) is computed given by,

$$\omega_{kc} = \sum_{i=1}^{k} \omega_{i_c} \tag{9}$$

The selection of feature vector in fusion is optimized by the minimization of divergence factor and having feature vector with relative higher weight value. the optimization for feature selection is given by,

$$Fsel \Rightarrow \{\arg\min(P[\gamma_i(f, f')]), ((\sum_{i=1}^{k} \omega_{i_c}) > \frac{A\omega}{k})\} \tag{10}$$

The process of feature selection presented optimizes the features with higher diversity and having weight associated higher than the relative weight value of all class $A\omega/k$. This condition selects features which has a variation in feature and are of more significance. The proposed feature fusion approach based on divergence factor and aggregated weight is outlined in the algorithm below.

ALGORITHM

Input: Feature set (f, f')
Result: selected fusion features
Process 1: Diversity feature selection
1. for each class,
2. Compute fusion feature for each patient 'i',

$$f_i = \{f_{ECGi}, f_{Ri}\}$$

3. Compute divergence of feature vector,

$$\gamma_i(f, f') = (f - f')^2$$

4. Converge the feature with the minimal factor

$$\arg\min(P[\gamma_i(f, f')])$$

5. Update the feature fusion for each group with minimal divergence,

$$G_u = f_i \Rightarrow G_u$$

Where 'u' define the group label varying 1-5.
6. Update the feature selection using weight allocation using process 2.

Process 2: Weighted selection approach $(Gu, \omega i)$
1. Associate weight (ωi) for each group Gu

$$Gu \Leftrightarrow \omega i$$

2. Compute aggregated weight factor $(A\omega)$,

$$A\omega = \sum_{i=1}^{k} \omega_i$$

3. compute each class aggregated weight,

$$\omega_{kc} = \sum_{i=1}^{k} \omega_{i_c}$$

4. Converge the feature selection of fusion,

$$Fsel \Rightarrow \{\arg\min(P[\gamma_i(f, f')]), (\left(\sum_{i=1}^{k} \omega_{i_c}\right) > \frac{A\omega}{k})\}$$

end Process1
end Process0
end

Selected features are distinct with variations and higher weight associated which is passed to a classifier unit. The classification operation is developed based on Ensemble deep learning model. The Neural Network is developed with training and testing phase. The network is trained for minimum class error and the NN model is developed with multiple layers with input, hidden and output layers. The network layout of the NN model is show in "Fig. 3".

The input to the NN model is the selected fusion features xi and weight value υi. For a given input set a set of weight is associated given as, $\upsilon = [\upsilon_1, \upsilon_2, \ldots\ldots, \upsilon_v]$ for the input $X = [x_1, x_2, \ldots., x_v]$

The output of the network is given by,

$$Y = f(\upsilon_t\, x)$$

or

$$Y = \sum_{i=1}^{v} \upsilon_i\, x_i \quad (11)$$

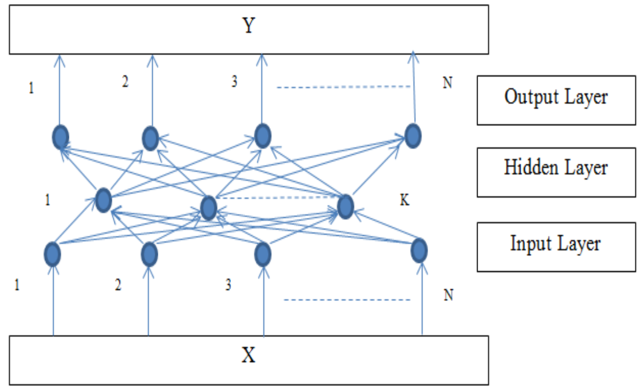

Fig. 3. Network Layout of the NN Model. Figure Illustrate the General Form of Neural Network with n-Input Nodes, N-Output Nodes and K Hidden Layers.

The output of the network is given as a bipolar representation of the NN model output given by,

$$Y = f(\upsilon t\, x) \quad (12)$$

$$Y = \begin{cases} -1, & x < 0 \\ 1, & x \geq 0 \end{cases} \quad (13)$$

A multi-level NN model is used for transition as illustrated in "Fig. 4".

The multi-level model process for error minimization based on the weight updation where a feed forward back propagated network for error minimization is developed. A weighted input-output relation with bias (g) passed to activation function (a) is used for mapping the output to input based on the updation. The relation of the input to output is given as,

$$Y_i = f\left(\sum_{i=1}^{n} \omega_i\, a\left(\sum_{i=1}^{k} \Phi_i\, x_i + g_i\right)\right) \quad (14)$$

The output is obtained as a function of updating weight variable Φ and bias value (g) and the class weight value is applied with the weight updation of NN model.

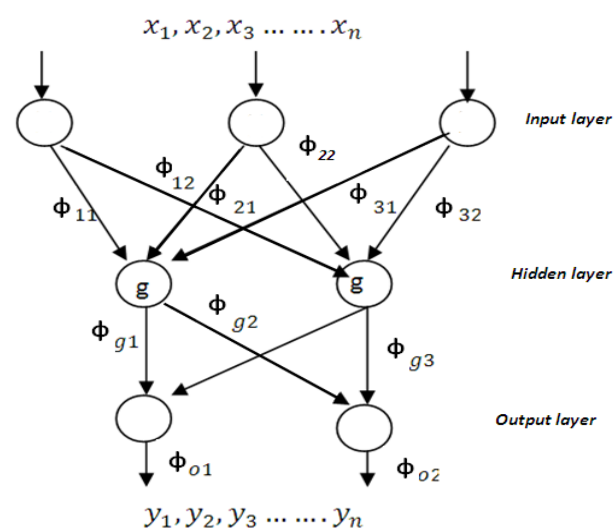

Fig. 4. Multi-Layer Network for Classification is Shown in Figure with Input X1-Xn and Output y1-yn.

V. Experimental Results

The presented approach of weighted feature fusion model (WFM) is tested for the presence or absence of heart disorderness. Simulation is developed for electronic records (ER) from updated Cleveland database consisting of 600 patient records, where each patient has 14 records of entry. The records are updated for time line observation and selected for fusion. ECG signals of 600 patients are taken from MIT database. ECG features are computed for peak values and time periods, which are used for fusion with the ER data. The proposed approach WFM is compared with the existing approach of embedded fusion model [26] and classifier models for performance evaluation. Few sets of ECG signals and ER used in training the network is shown in “Fig. 5” and Table II, respectively.

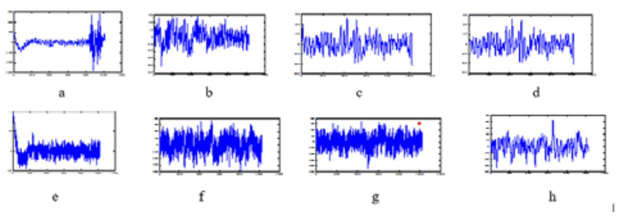

Fig. 5. ECG Signals from Database used for Training. The ECG Signals from MIT Database are used to Compute Peak Values and Time Periods.

Feature for each ECG signal is computed and fusion approach is applied with selective approach as outlined in Section IV. For testing an ECG signal is randomly selected from the database and corresponding ER record is read.

The ECG signal is processed for feature extraction, where the features are processed for fusion and selection and mapped to classifier model. NN classifier performs the classification for detection of disease diagnosis. The processing ECG signal is shown in “Fig. 6”.

The ECG signal is processed for peak detection and time period computation. Magnitude and time interval in reference to QRST measurement is computed. The magnitude plot for the peak values is illustrated in “Fig. 7”.

Computed features for the processing ECG signal are listed and a Mean value is computed to observe the variation of computing features for different ECG signals. Table III list the feature values for different test samples where the R peak counts (F1), Q-duration(T1), RR interval (T2), R-peak(F2), Q-peak(F3), S-peak(F4), P-location(F5), R-location(F6), S-location(F7), T-location(F8) and ST deviation(F9) is computed.

TABLE II. ER Record for the Patients used in Training. This ER Record Contain 14 different Attributes Fields

ER-Values	ER-filed													
	age	**sex**	**Chest pain**	**Trestbps**	**Chol**	**Fbs**	**Restecg**	**Thalach**	**Exang**	**Oldpeak**	**Slope**	**Ca**	**Thal**	**Num**
P1	64	0	3	140	313	0	0	133	0	0.2	1	0	7	0
P2	43	1	4	110	309	0	0	161	0	0	2	0	7	3
P3	45	1	4	128	259	0	2	143	0	3	2	3	3	1
P4	58	0	3	144	312	1	0	152	1	0	1	2	3	4
P5	50	0	2	142	200	0	2	134	0	0.9	1	0	7	1

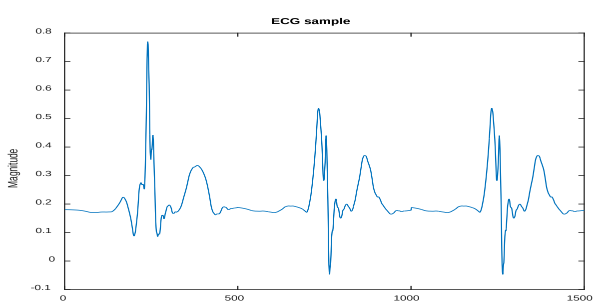

Fig. 6. Test Sample for Classification. Figure shows ECG Input Signal for Classifier.

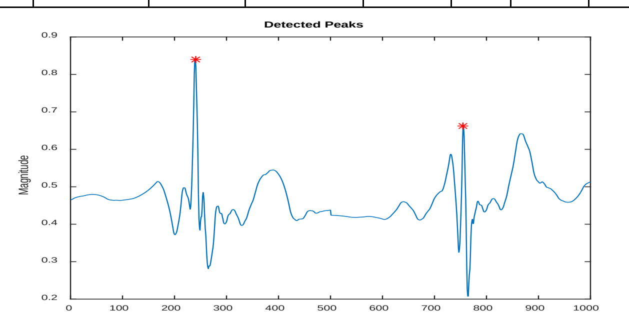

Fig. 7. Peak Level Representation of the Processing ECG Signal. Figure Illustrate that the Computed Peak Value of the Signal.

TABLE III. OBSERVATION FOR DIFFERENT FEATURE VECTORS COMPUTED FROM ECG SIGNAL. TABLE SHOWS THE LIST OF THE FEATURE VALUES FOR THE DIFFERENT TEST SAMPLES.

Sample	T1 (ms)	T2(ms)	F1	F2	F3	F4	F5	F6	F7	F8	F9	Mean
S1	585	578	2	0.86	0.62	0.66	273	351	347	361	0.13	227.2
S2	576	567	0.392	0.81	0.62	0.61	254	323	332	323	0.14	216.14
S3	534	573	0.37	0.85	0.62	0.66	251	356	343	334	0.12	217.60
S4	561	543	0.395	0.83	0.62	0.62	276	376	346	367	0.15	224.69
S5	588	571	0.36	0.89	0.62	0.69	212	398	323	369	0.16	223.97
S6	579	577	0.31	0.81	0.62	0.63	265	312	364	362	0.12	223.77
S7	565	567	0.67	0.80	0.62	0.67	223	353	368	367	0.16	222.35

The features are processed for fusion with ER and selection using WFM approach. The selected features passed to classifier model result in the classification of heart diseases. To observe the performance of the developed method retrieval accuracy, recall rate, precision and F-Score of the system is computed for 5-random test iterations. The accuracy of the system is measured as,

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{15}$$

The four parameters of observation (TP, TN, FP, FN) is derived from the confusion matrix presented in Table IV given as,

Where,

TP is the true positive.

TN is true negative

FP is false positive and

FN is false negative.

The precision for the developed system is defined by,

$$P = \frac{TP}{TP+FP} \tag{16}$$

Recall factor for the system is computed by,

$$R = \frac{TP}{TP+FN} \tag{17}$$

and the F-Score of the system is measured given by,

$$F = \frac{2*R.P}{R+P} \tag{18}$$

Observation for the developed system is listed in Tables V to VIII.

System accuracy of the proposed approach is shown in “Fig. 8” and it is observed to be improved by 0.7%. The accuracy is observed based on the selected feature due to divergence and weighted feature. As the features of critical observations are retained rather than entropy measure the accuracy of the proposed system is improved.

TABLE IV. CONFUSION MATRIX FOR THE ANALYSIS

Diagnosis	Effective	Not-Effective
Effective	TP	FN
Not-Effective	TN	FP

TABLE V. SYSTEM ACCURACY OF THE WFM APPROACH. THE PROPOSED WFM APPROACH HAS 99.2% ACCURACY, WHICH SHOWS0.71% INCREASE IN ACCURACY THAN THAT OF FUSION MODEL

SVM [26]	L-Regression [26]	Decision Tree [26]	Naïve Bayes [26]	Fusion model [26]	Proposed WFM
84.4	92.2	77.6	83.4	98.5	99.2

TABLE VI. SYSTEM RECALL RATE OF THE DEVELOPED APPROACH. THE PROPOSED WFM APPROACH HAS 1.97% INCREASE IN RECALL THAN THAT OF FUSION MODEL

SVM [26]	L-Regression [26]	Decision Tree [26]	Naïve Bayes [26]	Fusion model [26]	Proposed WFM
81.5	95.2	77.7	78.5	96.4	98.3

TABLE VII. SYSTEM PRECISION OF THE DEVELOPED APPROACH. THE PROPOSED WFM APPROACH HAS 98.9% PRECISION

SVM [26]	L-Regression [26]	Decision Tree [26]	Naïve Bayes [26]	Fusion model [26]	Proposed WFM
87.5	89.2	84.6	88.8	98.2	98.9

TABLE VIII. SYSTEM F-SCORE OF THE DEVELOPED APPROACH. THE PROPOSED WFM APPROACH HAS 98.4% F-SCORE

SVM [26]	L-Regression [26]	Decision Tree [26]	Naïve Bayes [26]	Fusion model [26]	Proposed WFM
84.5	92.2	77.6	83.4	97.2	98.4

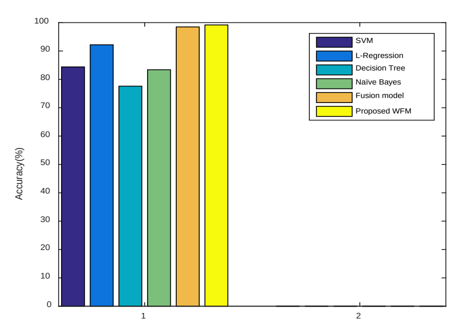

Fig. 8. Figure shows the Accuracy Plot for WFM Approach. The Developed System Achieves 99.2% Accuracy.

System recall, and precision shown in “Fig. 9, 10” is observed to have an improved by 2%, and 0.7% respectively. The selective approach by weighted method results in improvement of the system parameters. The F-Score of the system is improved by 1.2% as shown in “Fig. 11”.

Observation for the developed approach for different time period of observation is listed in Table IX. The variation of time period in ECG monitoring has significance on the classification performance is shown in “Fig. 12”. For a short period, observation of 10ms the accuracy obtained is 97%, wherein for 15ms observation it is obtained to 98% and for a higher time period observation of 20ms the accuracy is retained to 98%, signifying an average period observation has a maximum accuracy and long period observation has same effect as redundant features are observed. The time period for longer period is observed to be higher compared to short period observation. Selection of the features with high divergence and weight parameter result in selection of feature vectors which result in lower time for classification.

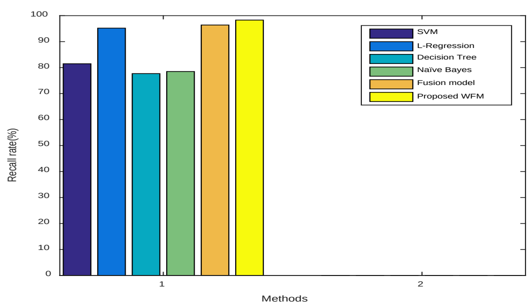

Fig. 9. Recall Rate Plot for WFM Approach. Figure shows the Recall Rate of Developed System Up to 98.3%.

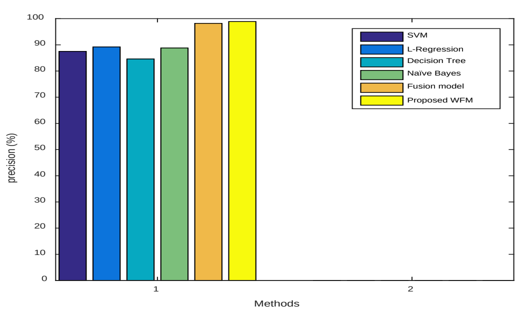

Fig. 10. Precision Plot for WFM Approach. Figure Shows the System Precision of Developed System Up to 98.9%.

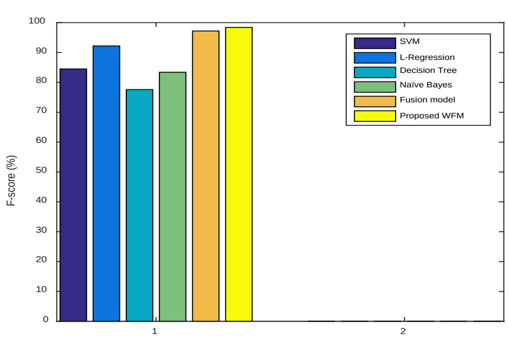

Fig. 11. F-Score Plot for WFM Approach. Figure shows the F-Score of Developed System Up to 98.4%.

TABLE IX. OBSERVATION FOR ECG SIGNAL WITH DIFFERENT TIME PERIODS. THE OBSERVATIONS OF ECG SIGNAL WITH TIME PERIODS 10MS, 15MS, 20MS

Observing time period	**Accuracy (%)**	**Recall**	**Precision**	**F-Measure**	**Time (sec)**
10ms	97.3	95.3	98.1	96.8	10.6
15ms	98.6	97.4	98.6	98.2	14.5
20ms	98.7	97.6	98.8	98.4	18.3

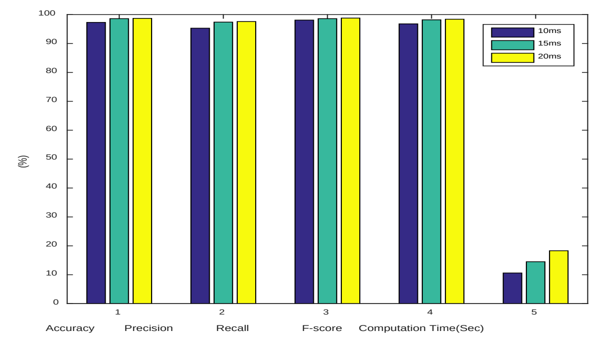

Fig. 12. Observation for different Time Period of Sample. The Figure Illustrates the Observations of ECG Signal with Time Periods 10ms, 15ms, 20ms.

VI. CONCLUSION

An approach for feature fusion based on the selection of feature vector and class attribute is presented. The process of weighted clustering based on information gain and updated feature is presented. This approach illustrated an enhancement of feature selection and improvement in accuracy of the system based on the observations obtained. The system accuracy is obtained to be improved based on the selected feature and fusion of multiple parameters in observation. The significant illustration of feature selection has given dual advantage of feature selection and classification performance for heart disease diagnosis. The selective method of feature selection based on divergence and weighted method provide a more accurate selection of fusion feature as the criticality factor is monitored based on associated weight factor which results in the improvement of system performance. In future, the proposed approach will be extended with varying conditions of heart monitoring with patient having multiple diseases and varying signal input conditions such as magnitude variations and signal wandering distortions.

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