Optimal Classification Process using Fuzzy C-Means Neural Network for Effective Prediction of Cardiac Arrest Due to Diabetes

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In recent scores, diabetes mellitus (DM) is regarded as a chronic illness and one of the leading critical health challenges throughout the earth. About eighty percent of demise occurs because of DM (Type II) which could be avoided by the earlier diagnosis of persons with this threat. Nevertheless, presently machine learning techniques can be employed for diabetics' detection very precisely. We are proffering a health care monitoring system comprising ECG sensors. The criteria that have a considerable volume of significance will be sensed by ECG sensors that remain important for remote monitoring of sick person. A mobile app observance will be employed for consistently monitoring sick person's ECG and diverse data extraction approaches will be executed upon ECG wave for extracting features to properly prognosis heart illnesses. Hence, this study proffers employment of a metaheuristic optimization algorithm called Real Coded Binary Ant Bee Colony (RC-BABC) for optimized feature choosing, and Relief methodology will be employed for excerpting features and computing the features' scores centered upon disparities in feature values and class values betwixt nearby cases. An effectual attempt will be carried out for detecting cardiac demist at early phases emerging out of intensity of DMin which feature prognosis before heart rate variability assessment will be executed. DM's features would be analyzed out of diabetic's data set for detecting reason for abrupt cardiac arrest. Next, the excerpted features are classified employing Fuzzy C-means Neural Network (FCNN). The performance analysis is carried out to exhibit that FCNN executes properly in prognosticating illnesses. The proffered FCNN paradigm attains 97% and 84% of testing and training (tt) accuracy, 93% and 82% of ttspecificity, 95% and 81% of ttsensitivity and 92% and 85% of ttF1-score.

Keywords: cardiac arrest, diabetics, classification, neural network, preprocessing, optimization, feature score

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1. Introduction

Cardiovascular disease (CVD) remains a fatal situation. This remains the primary reason for the demise internationally having thirty percent of entire international demises ascribed to it measuring up to seventeen million demises internationally [1]. Furthermore, demise pertained to CVDs has been predicted to increase up to twenty-two million in 2030 when immediate actions are unconsidered. Statistics out of the American Cardiac Association (AHA) reveal that around fifty percent of American grownups are affected by CVDs [2]. Meantime, it remains arduous for diagnosing cardiac arrest (CA) because of multiple contributing threats inclusive of high blood pressure (BP), diabetes, high cholesterol, arrhythmia, and so on [3]. Nevertheless, these stakes could be lessened via suitable way of life modifications. CA's typical indications are difficulty in breathing, swelling feet, and fatigue. Initial diagnosis remains arduous yet could notably enhance a sick person's survivability. Hence, optimized diagnosis via machine learning (ML)-related prognosis paradigms are lately promoted by physicians for decreasing the mortality toll and optimizing the medical decision-taking procedure.

The ML employment in medical decision-taking could assist physicians in diagnosing CA threats and give required therapies and suggestions for governing the threat [4]. For attaining this, e-fitness registers are employed for training ML paradigms and learning the hidden associations within the data. Some publically attainable CA databases and multiple prognostic paradigms were established over time [5]. Meantime, analysts and inventors yet possess hardship in acquiring elevated prognostic execution and detecting the very pertinent CA threat [6]. An array of important featurescould be acquired by implementing feature learning (FL) approaches, and the consequential lower-dimensional feature portrayal could clarify the classification job. FL or portrayal learning assures the paradigm automatedly finds the necessary portrayal for effectual feature identification and input data (ID) classification.

The Internet of Medical Things (IoMT) remains the envision of giving a finer and extra potent fitness observation system. IoMT remains the incorporation of clinical gadgets via Wi-Fi and allows device-to-device (D2D) communication. Recently, the extreme arduous problem remains the time required for network services. The 3D video could be downloaded at intermittent interims by considering the recent technical fads. The gathered hefty data having lesser delaywill be attained for the precise data measuring.This would raise the gadget resource allotment capability and provides swifter speed for the heterogeneous networks (HNs). The IoMT consists of diverse HNs, for example, Wi-Fi, Bluetooth, ZigBee, and the rest of the cellular forums. The D2D communication remains the IoMT forum'score having great efficacy and reliableness. An intelligent medical system remains to provide lower delay and great throughput and reliableness that remain more significant for an effectual and precise prognosis and consultation. The crucial time assessment remains the chief criterion to be regarded for exigency medical implementations. The immensely dependable and delay-tolerant communication and data transfer could be attained through IoT-driven wearable gadgets.

This study proffers a novel illness prognosis paradigm, which contains 3 stages – preprocessing, enhanced feature extraction (FE), and classification. Initially, the provided database will be preprocessed through data transition out of which the rules are created. Next, the enhanced features will be chosen by a novel presented feature selection (FS)and FE. Lastly, the chosen enhanced features will be put through the classifier; accordingly, the prognosis paradigm provides the classified result further precisely. The aims of this study are: to execute many experimentations for enhancing the execution of the prognostic classifiers for CA detection by employing the rest of the FS algorithms (FSAs)and augmentation approaches concerning the precision, detection execution, and optimize the computing duration for handling the intricate non-linear issues having a fine resilience and versatility with the finest augmentation algorithm.

This work comprises of the following segments: Segment 1 exhibits the CA's overview, FE function, and CA prognosis enhancement, Segment 2 indicates the present approaches for CA prognosis alongside its constraints, Segment 3 provides FE and FS approaches, Segment 4 presents the effective experimental assessment, and Segment 5 sums up with a conclusion and prospective study.

2. Associated studies

The study [7] employs a genetic algorithm for choosing features out of the Cleveland database. This technique provides a subcategory of 7 features that were implemented in 4 machine learning methodologies: SVM, multilayer perceptron, J48, and K Nearest Neighbors (KNN) for constructing paradigms for heart-illness prognosis. The authors assessed the paradigms employing ten-fold cross-validation and correlated the outcomes to paradigms constructed upon the initial feature set (FS) and also FSs were chosen employing a few generally utilized FS approaches.

The study [8] presents machine learning as a substitute to the launched heart-illness threat analysis methodologies. The writers used a database obtained out of the United Kingdom's Clinical Practice Research Data link in R Studio and tested 4 uncomplicated classification algorithms – logistic regression, random forest (RF), gradient boosting machines, and neural networks (NNs), and also the American Cardiac Association/American College of Cardiology (ACC/AHA) reference paradigm. The data have been divided as – seventy-five percent into a training arrayand twenty-five percent into a confirmation array. The authors noticed that entire machine learning methodologies executed finer than the ACC/AHA paradigm.

The study [9] tests 4 disparate classification approaches upon the cardial-illness database - Naïve Bayes, KNN, decision tree, and bagging. Instead of employing an FSA for selecting the very meticulously important features, the authors selected features centered upon domain knowledge. The authors noticed that the technique enhanced the precision of their paradigms created with Naïve Bayesand KNN yet lessened the accuracy of the decision tree and bagging paradigms. The study [10] generated an architecture for cardial-illness classification, which encompasses FE employing Principle Component Analysis (PCA). The writers mention the advantages of lessening the data size – enhanced classifier's prognosis precision and lessening the prognosis' computing charge.

The study [11] implemented PCA towards a database of typically renowned cardial-illness threat attributes upon a minority populace of Punjabi Indians over 3 generations. The database incorporated features like weight, waist wideness, body mass index, BP, and pulse rate. The study [12] employs FS with a Chi-squared feature evaluator within conjunction with the RF machine learning algorithm for constructing a paradigm cardial-illness prognosis upon the stat log cardial-illness database.

The study [13] employs PCA within conjunction having FS for excerpting PCA databases out of diverse disparate feature arrays, once more centered upon the Cleveland cardial-illness database. On the whole, the authors acquired 6 disparate databases containing the initial array having fourteen features. Next, the regression and a feed-forward NN(FFNN) algorithm have been implemented to every database for generating a prognostic paradigm. The authors noticed that one among the PCA databases, while employed with the FFNN, attained an accuracy of95.2%.

3. Proffered methodology

At first, the CA with the diabetic database will be performed to seek the classes. The pre processing occurs for lessening Appropriate Learning Size (ALS) and seeking the lacking values. Then, FS will be performed employing Real Coded Binary Ant Bee Colony (RCBABC). Subsequent to choosing the features, the needed features will be excerpted employing Relief methodology (RM) alongside the aid of score computation. Lastly, Fuzzy C-Means Neural Network (FCMNN) assists in appropriately classifying the CA threat.

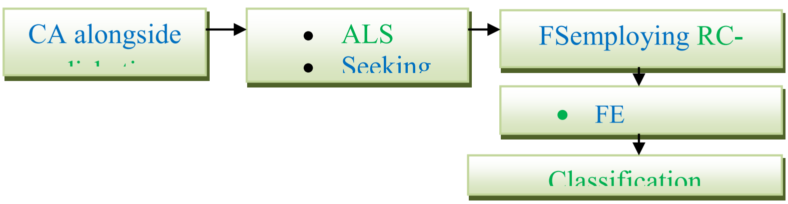

Fig. 1: Block schematic illustration to classify CA threat

Hypertension (Hpt) remains the major reason for illness and fatality internationally. Integrating precise blood pressure (Bp) measuring inside customer-grade wearables possess the potentiality for enhancing checkup for Hpt and detecting nocturnal or exercise Hpt that are bound to bad results. For office Bp measuring, sick persons have been made to sit and wear the Heart Guide wristwatch and the conventional Bp measuring gadget fixed in the non-predominant hand and Bp readings have been measured two times by every gadget in alternate thirty to sixty-second interims. For ambulatory Bp measurings, sick persons have been provided an ambulatory, brachium device, which calculates Bp at thirty-minute interims over twenty-four-hour and has been informed to employ the Heart Guide gadget subsequent to every ambulatory Bp measuring not less than ten times when awake. The biochemical sensor could calculate body fluid electrolytes employing electrochemical transducers providing precious data regarding plasma volume condition and analyte concentrations. Nevertheless, the precision of these sensors modifies with skin temperature, skin adulterant with dirt, shriveled sweat, or the rest of the stuff and hair denseness. Biomechanical sensors (BmS)integrated into clothes or shoes, like ballistocardiograms, seismocardiograms, and dielectric sensors, were established in a trial to automatically and consistently calculate factors like cardiac output, lung fluid volume, and weight that can remain advantageous in handling situations like Heart failure(HF). The rest of the BmS like adaptable and tattoo-like sensors centered upon microfluidics as well as remain hopeful for non-intrusive, hemodynamic, and consistent observation. Nevertheless, these entire emergent sensors yet need profuse medical substantiation.

3.1 Database Gathering

The database employed in this study remained the 'CA with diabetic database' of the UCI ML repository. This contained a label known as coronary angiography and seventy-four individual features. This indicated in any case a sick person possesses the existence or non-existence of CA. The CA existence amalgamated the values one, two, three, and four out of the initial databases. For the testing, sick persons provided historical data and were manually tested by physicians. As a function of the conventions, 3 nonintrusive tests have been performed – exercise electrocardiogram, exercise thallium scintigraphy, and coronary calcium fluoroscopy. The heart specialist elucidated the coronary angiogram outcomes never aware of the nonintrusive outcomes. The feature regions are as ensues.

1. **Age**: exhibits a person's age
2. **Sex**: exhibits a person's gender employing the ensuing form:
   1 = male
   0 = female
3. **Chest-pain kind**: exhibits the chest-pain kind underwent by a person employing the ensuring form:
   1 = typical angina
   2 = atypical angina
   3 = non-anginal pain
   4 = asymptotic
4. **Resting Blood Pressure**: exhibits a person's resting BP value in mmHg (unit)
5. **Serum Cholesterol**: exhibits the serum cholesterol in mg/dl (unit)
6. **Fasting Blood Sugar**: correlates a person's fasting blood sugar value with 120mg/dl.
   When fasting blood sugar > 120mg/dl then : 1 (true)
   else : 0 (false)
7. **Resting ECG**: exhibits resting electrocardiographic outcomes
   0 = normal
   1 = having ST-T wave abnormality
   2 = left ventricular hyperthrophy
8. **Exercise-inducedangina** :
   1 = yes
   0 = no
9. **Peak exercise segment** :
   1 = upsloping
   2 = flat
   3 = downsloping
10. Diabetes timespan(years) – 20 years, 30 years, 40 years
11. Insulin treatment:1- yes,0-no, Oral hypoglycemic agent treatment: 1- yes,0-no

12. Diabetic autonomic neuropathy: 1- yes,0-no
13. **CA detection**: exhibits in any case a person is struggling with CA or not:
    0 = non-existence
    1= existence.

3.2 Preprocessing

Provided a huge database comprising N records and K local learners, the initial phase in Adaptive Two-Stage Data Slicing remains to execute the global data slicing (GDS) upon the huge database to assign data equally amidst accessible local learners (LLs)for load balancing and consequential learning. Every LL would obtain a GDS of N/K rows as the input for LL. Next, the ALS value will be computed for attaining every local's suitable dimension. The GDS upon every LL can be adaptably split into several local data slices (DSs)of size ALS (s-ALS)for effectual and dispensed learning. Provided K LLs, every LL would obtain Nd DSs for dispensed learning in which each DS will be s-ALS. Nd is computed as,

$$\text{Nd} = \frac{N}{K*ALS}$$

The preprocessing in corporates dealing with lacking values, target class transition, and data discretization.

- Dealing with lacking values: There remain five manners to deal with the lacking data – (a) deleting rows, (b) substituting with mean/median/mode, (c) designating a distinct class, (d) prognosticating the lacking values, and (e) employing algorithms that reinforce lacking values.
- Target class transition: The target class comprises values (0 to 4) in which zero refers to disease-free (without CA) and the rest of the values refer to the existence of the disease at diverse levels. Attention will be on the CA's existence or non-existence; hence, it is required to constrain the class to (0, 1). The level (1 to 4) was transformed into one.
- Data Discretization: In the database, five from fourteen features remain continual. Variables within Variable-order Bayesian network (VOBN) paradigms remain individual naturally, and hence, it is necessary for creating the continual data classific. We depend upon specialist knowledge for discretizing data. The continual features include age, trestsbp, chol, thalach, and old peak.

3.3 RCBABC for optimized FS

An original populace $M = [X1, X2, \ldots., Xm]$of m solutions or food source locations will be produced haphazardly in the multiple-dimensional solution area in which m portrays the populace dimension. Every solution $Xi = Pi1, Pi2 \ldots. Pij \ldots PiD, (i = 1, 2, \ldots, m \ and \ j = 1,2, \ldots D)$will be portrayed by a D-dimensional vector in which D represents the criteria quantity that to be optimized. In the present study, for the optimization issue, D remains equivalent to the features' quantity N. Every solution vector's components that are indicated as xij remains the feature modules' actual output, and these will be dispensed evenly betwixt their highest and lowest production limitations. For FS, this remains favourable to search for the finest precision employing the minimal feasible features' quantity. For this cause, the proffered methodology ensues the forward search approach.

- Present feature subset (FSS) of food sources (FdS) to the classifier and employ accuracy as fitness: every FdS' FSS will be presented to the classifier, and accuracy will be saved as the food source's fitness.

- Fitness function – Assess the fitness value of every FdS location correlating to the utilized bees within the colony.

$$Fitness = A[1 - \%cost] + B[1 - \% \ error]$$

$$Error = \sum_{i=1}^{n} pi - pl - pd$$

$$\% \ error = \frac{stringerror - minerror}{maxerror - min \ error}$$

in which A and B denote positive weighing coefficients, string error denotes the independent string's error in encountering the power balance constraint (PBC), min error denotes the minimal constraint error (CE)inside the populace, and max error denotes the maximal CE inside the populace.

- Limitation dealing– the altered location will be later inspected for PBC and producing module's ability constraint defiance. When the PBC remains discontented, the error will be included in whatsoever modules selected haphazardly. It carries on till the PBC could have contended. Meantime, the power outputs will be inspected for module ability limit defiance and fixed to the maximum limits in the event of defiance. Furthermore, the prohibited operating zone constraint will be inspected and when whatsoever module's power output comes within the prohibited zone, they will be fixed to the top or bottom limit of the zone.

3.4 Feature extraction

FE remains the procedure of generating a novel and tiny array of variables having the objective to catch the very beneficial data, which are available in the initial variables (IVs), for prognosticating the result. The novel variables will be generated by implementing a transition towards the IVs. The transitioned variables portray IVs' projections into a novel variable area in which the unique result sets possess a finer division correlated to the IV area. RM will be employed to excerpt the features and compute the feature scores (FtS) centered upon the disparities within feature values and class values betwixt adjacent cases. Remaining in a similar class remains extra probably for the nearer distances to a provided distance. When a feature remains beneficial, it will be anticipated that the nearest distances of a similar class remain nearer to the range provided all over the feature than the nearest distances of the entire classes. Hence, the provided feature's weight (severity) can be computed as,

$$W = W - diff(xij, near\_hitij)2 \; + diff(xij, near\_missij)2 \; /m$$

M mentions the sample dimension (haphazardly chosen out of the training set's subset. diff(x_{ij},near_hit$_{ij}$), diff(x_{ij},near_miss$_{ij}$)represents the disparity betwixt the feature values inside haphazardly chosen j distance and feature's near_hit$_{ij}$value inside the nearest training sample (TS)within a similar class. Simultaneously, diff(x_{ij},near_miss$_{ij}$)denotes the nearest TS value out of disparate classes. For a beneficial feature, near_miss$_{ij}$values will be predicted to remain so near to every other. When a feature remains useless, both disparities will be predicted to consume about the similar dispensation that attempts in choosing features, which possess the nearest pertinence with class labels (CLs). Simultaneously, this remains a filtering methodology, which attempts to lessen redundancy amidst the chosen features. The algorithm analysis every feature and CLvector (CLV)as an individual concurrence and employs mutual data (MD) I(x, y) for calculating similarity level betwixt the 2 features or a feature and CLV. MDcan be described by,

$$\mathrm{I(x,y)}=\sum_{I,J}^{n} \mathrm{p(x,y)log}\frac{\mathrm{p(xi,yj)}}{\mathrm{p(xi)p(yj)}}$$

where $\mathrm{p(xi)}$and$\mathrm{p(yj)}$ portray feature functions, and $\mathrm{p(xi,yj)}$portray the combined probability dispensation. The MDvalue remains zero in which 2 haphazard variables remain totally individual.

$$Max\, I(x,y) \;=\; \frac{1}{s}\sum_{k=0}^{n} I(h,i)$$

The next one remains minimal redundancy Min I(x,y).

$$Min\, I(x,y) \;=\; \frac{1}{s}\sum_{k=0}^{n} I(i,j)$$
$$Where, h = \;\{h1, h2 \ldots . hk\}$$

FtS can be computed by discerning reconstruction error (RE) subsequent to class-wise low-dimensional embedding (LDE), and this employs the RE characteristic, which varies by class. The RE for every database can be attained by computing the disparity betwixt rebuilt data and initial data. The feature-wise REs (FWREs)within every database can be computed by the FWREs total for every feature. Lastly, the FWREs of the entire data and the data's error for every class will be employed for deriving the last FtS as illustrated in figure 2.

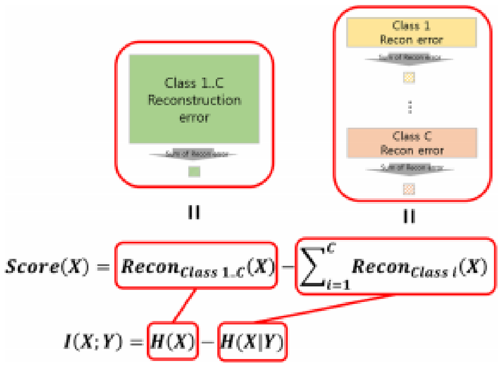

Fig. 2: FS discernment in RM

$\text{Recon}_{\text{Class}}$ 1.C(X) remains a terminology of the RE subsequent to the data X's LDE. $\sum_{i=0}^{c}$ ReconClass 1. (X) remains the total of the terminologies implemented to every class individually. In other words, the initial portion will be computed devoid of label data (LD) and correlates to H(X). The next portion remains a RE within the status provided by the LD, and this correlates to the conditional entropy below the LD. When this remains related with the score equation in figure 3, the ensuring will be acquired:

$$Score\ (x) = Recon\ class\ 1.C(X) - \sum_{1}^{c} Reconi(x)$$

$$= Recon\ 1.C(Fj) - \sum_{1}^{c} \sum_{1}^{F} Reconi(Fi)$$

$$= Recon1.C(Fj) - \sum_{1}^{F} \sum_{1}^{C} Reconi(Fi)$$

The total score (TS) of X remains the scores' totalcomputed for every feature. The score computed for every feature remains the input of the feature to the (TS); hence, this could be known as the FtS, which could differentiate the label.

4. Classification employing the FCWN classifier

Ensuring the features choosing procedure, FCMNN can be employed for the chosen features classification. FCMNN classifier can be supplied with every chosen feature as input. The weight remains a haphazardly designated value that is linked by each input. After the hidden nodes of the hidden layer (HL) attain the intention of summing the multiplication of the input value and any node's weight vector (WV), which remains linked to it. Outcomes will be attained out of the haphazard weight values that advance the back-propagation (BPg) procedure. The optimization will be performed in this manner. The activation procedure will be involved afterward, and the output layer (OL)will be associated with succeeding layers. The weight forcefully affects its classifier's output. The algorithmic phase within the FCMNN classification is as ensues.

Phase I – The selected features' values alongside its weights can be portrayed in the equations (1) and (2) as,

$Fi = \{F1, 2, F3 \ldots\ldots Fn\}$ (1)

$Wi = \{W1, W2, W3 \ldots\ldots Wn\}$ (2)

in this, the input values are indicated by Fiindicating $n$chosen features. $1, 2, F3 \ldots Fn$indicates the Fi. The weighted value remains portrayed by Withat specify $n$equal weight $W1, W2, W3 \ldots\ldots Wn$.

Phase II – Obtain the inputs' result and haphazardly choose WVs and assess:

$M = \sum Fini{-1}\, Wi$

in this, Mindicates the total value.

Phase III: Activation function (AF) will be defined.

$Afi = (\sum FiWi)\ ni{=}1$ (3)

$Ci = e^{-Fi2}$ (4)

in this, Afidenotes the AF and the Fiexponent is indicated by Ci. The activation function includes the Gaussian function as its set employed in the present study.

Phase IV – The succeeding HL's output is assessed by,

$Yi = Bi + \sum CiWi$ (5)

in this, Birepresents the biasing value, and Wirepresents the weights thatexist betwixt the input layer and HL.

Phase V – Here, three steps are executed for each layer within the network. Finally, the output unit will be analyzed by totaling all input weights data to attain the neurons' value within the OL.

$Ri = Bi + \sum OiWj$ (6)

in this Oiportrays the layer value, which leads the OL, Wjportrays the HL weights, and Riportrays the output unit.

Phase VI – The network's output (NwO) will be compared with the objected value (OV). The NwO and OV are modified amidst the values employed previously and called the error data (ED). This can be calculated as,

$Er = Di - Ri$ (7)

in this Errepresents the ED and Direpresents the objected result.

Phase VII – Here, the consequential component value will be compared with the OV. Discerning the error lined and relies on this, $\delta i$is computed, which is equally employed for indicating the output error back towards all the network modules.

$\delta i = Er\ [(Ri)]$ (8)

Phase VIII: The BPgalgorithm progresses the weight correction (WC)as,

$Wci = (Fi)$ (9)

in this Wciindicates the WC feature, αindicates the momentum, and δiindicates the error that is distributed within the network.

$Fn = \sum_{i=1}^{n} \sum_{j=1}^{c} pij(ai - cj),$ (10)

In the equation (10), nportrays whatsoever actual numeral greater than one, pijportrays the membership degree of ai within the cluster F, aiportrays the $i^{th}$of computed dimension data, $c_j$portrays the cluster's d^{th}dimensioncenter, and $||*||$portrays the normalization conveying the similarity amidst whatsoever data computed.

Next, the membership pijand cluster cjwill be updatedby,

$\text{Pij} = \frac{1}{\sum_{k=1}^{n} \frac{ai-cj}{ai-ck}}$ (11)

$\text{Cj} = \frac{\sum_{i=1}^{n} pij(m)}{ck}$ (12)

The updating procedure would execute till the equation (13) will be contented.

Max (ij) {pij(k+1)-pij(k)<n (13)

While doing training, samples of one batch will be supplied to the network every moment, and the average value of the loss of thesample within the batch will be taken into consideration as the batch loss (BL). In spite of its simpleness, it could not distinguish the losses out of disparate samples within a batch while doing training and additionally enhance the training precision. The batch sample loss will be classified in decreasing sequence, and the biggest values are made a mean like the last loss.

This highlights unclear samples with big loss values while doing training and enhances their classification precision..

5. Experimental assessment

For the arrithyima prognosis, the results and discourse of the proposed FCMNN network will be employed and the victory is analyzed with diverse execution metrics. Lastly, there remains an experiment for equalizing the effectiveness of the proffered paradigm with the rest of the DL's implementations. Performance metrics like accuracy, sensitivity, specificity, and F1-score are employed for analyzing the efficiency of the proffered model.

Accuracy remains the ratio of comprehensive subjects that are precisely detected.

$$Accuracy = \frac{\sum TP + \sum TN}{\sum TP + \sum TN + \sum FP + \sum FN} \tag{22}$$

The sensitivity indicates the sick persons' count having CA.

$$Sensitivity = \frac{\sum TP}{\sum TP + \sum FN} \tag{23}$$

Specificity refers to the percentage of persons having none negative disease. Recall remains similar as specificity.

$$Specificity = \frac{\sum TN}{\sum TN + \sum FP} \tag{24}$$

F1-score remains the harmonic means of accuracy and recall.

$$F1 - Score = \frac{2 \times Recall \times Precision}{Recall \times Precision} \tag{25}$$

Here, TP (true positive) and FP (false positive) portray the right and wrong classification of CA cases. Likewise, TN (true negative) and FN (false negative) portray the percentage of cases without CA who are rightly and wrongly classified, accordingly.

Table 1 exhibits the proffered FCMNN paradigm's execution with disparate performance metrics and its data upon training and testing (T&T). The metrics employed for analysis remain accuracy, specificity, sensitivity, and F1-score.

Table 1: FCMNN execution for hundred epoch dimension

Performance Metrics	**Data**	
	Testing (%)	**Training (%)**
Accuracy	94	89
Specificity	98	91
Sensitivity	94	82
F1-Score	90	84

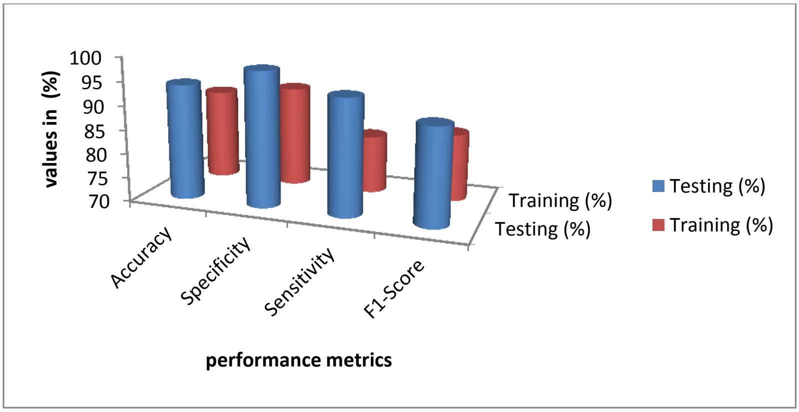

Fig. 3: T&T paradigm correlation for one hundred epochs

Figure 3 illustrates the proffered FCMNN T&T paradigm for one hundred epochs. The X-axis exhibits the performance metrics and the Y-axis exhibits the values attained. The blue colour denotes the testing data (TtD) and the maroon colour denotes the training data (TnD). The proffered FCMNN paradigm attains 94%and 98% of T&T accuracy, 98% and 91% of T&T specificity, 94% and 82% of T&T sensitivity, and 90% and 84% of T&T F1-score.

Table 2: FCMNN execution for epoch dimension = 200 and300

Performance Metrics	**Epochs=200**		**Epochs=300**	
	Testing (%)	**Training (%)**	**Testing (%)**	**Training (%)**
Accuracy	94	80	97	84
Specificity	93	84	93	82
Sensitivity	96	87	95	81
F1-Score	93	84	92	85

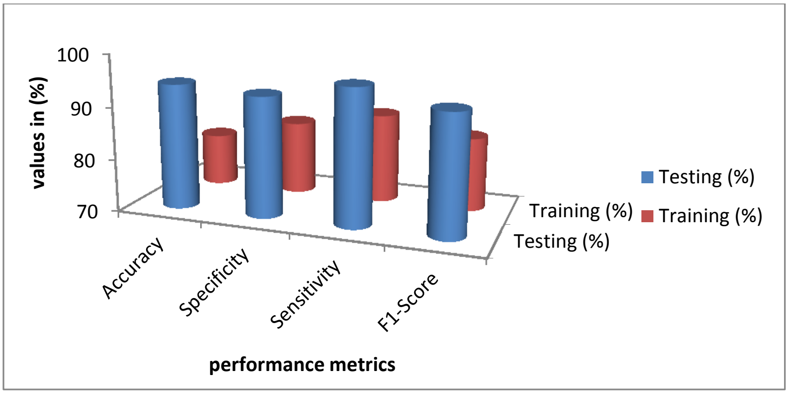

Fig. 4: T&T paradigm correlation for two hundred epochs

Figure 4 illustrates the proffered FCMNN T&T paradigm for two hundred epochs. The X-axis exhibits the performance metrics and the Y-axis exhibits the values attained. The blue colour denotes the TtD and the maroon colour denotes the TnD. The proffered FCMNN paradigm attains 94% and 80% of T&T accuracy, 93% and 84% of T&T specificity, 96% and 87% of T&T sensitivity, and 93% and 84% of T&T F1-score.

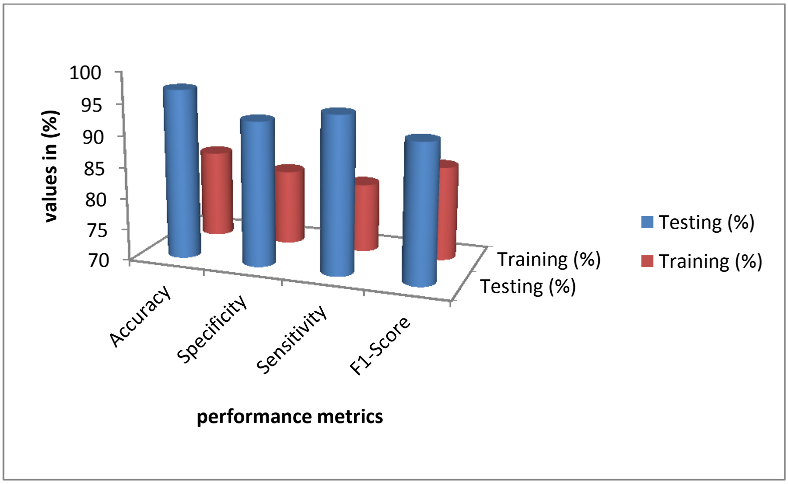

Fig. 5: T&T paradigm correlation for three hundred epochs

Figure 5 illustrates the proffered FCMNN T&T paradigm for three hundred epochs. The X-axis exhibits the performance metrics and the Y-axis exhibits the values attained. The blue color denotes the TtDand the strooncolor denotes the TnD. The proffered FCMNN paradigm attains 97% and 84% of T&T accuracy, 93% and 82% of T&T specificity, 95% and 81% of T&T sensitivity, and 92% and 85% of T&T F1-score.

Conclusion

MOA's efficacy is confirmed by resolving multiple problems concerning text clustering. Yet, local optima trapping remains feasible since the concentration remains upon global search instead of local search, that is, exploration rather than exploitation. This study proffers MOA called RCBABC for diabetes data that resulted in the CA threat's prognostic assessment centered upon blood vessels, cardial nerves, and cardial nerve injuries. Next, an FCMNN was launched in which the classification was performed employing CNN. Through this classification, the typical and atypical ranges of diabetes were classified; the former was updated to the medical center dataset, and, for the latter, the cardiac nerve and blood vessel injury were assessed. Henceforward, hybrid DL methodologies could be employed to additionally enhance the paradigm's efficacy.

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