

# Prediction Model for Cardiovascular Disease Risk in Type-2 Diabetic Patients Using a Hybrid Artificial Bee Colony Model and Semi-Supervised Learning

Kumud Pant<sup>1</sup>, Dibyahash Bordoloi<sup>2</sup>, Bhasker Pant<sup>3</sup>

<sup>1</sup>Department of Biotechnology, Graphic Era Deemed to be University, Dehradun, Uttarakhand India, 248002

<sup>2</sup>Head of the Department, Department of Computer Science & Engineering, Graphic Era Hill University, Dehradun, Uttarakhand India, 248002

<sup>3</sup>Department of Computer Science & Engineering, Graphic Era Deemed to be University, Dehradun, Uttarakhand India, 248002

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## ABSTRACT

A significant risk factor for death in people with diabetes is cardiovascular disease (CVD). More than 22% of persons with type 2 diabetes mellitus also have cardiovascular disease, and it is thought that the two conditions are causally related. However, not all of the research put enough emphasis on semi-supervised learning techniques that use feature selection strategies to improve the prediction accuracy of classification techniques. This study was out to better predict outcomes by identifying key CVD variables affecting type 2 diabetes management. Patient data is preprocessed and dimensionality reduced using Kullback-Leibler divergence (KLD)-principal component analysis (PCA) in the proposed methods; attribute values are measured using kernel density estimation (KDE), which measures attribute values using a probability mass function with a Gaussian kernel function; and feature selection is carried out utilising an artificial bee colony with differential evolution (ABC-DE). Semi-supervised Modified Self-Organizing Feature Map Neural Network (MSOFMNN) classification technique is used to the data after it has been clustered using the Improved Fuzzy C Means (IFCM) clustering algorithm in a hybrid prediction model to verify the selected class label of the input data. With improved prediction accuracy and reduced error rate, the proposed technique investigates the behavioural aspects that lead to CVD risk factors in people with type 2 diabetes (T2D).

**Keywords:** Artificial Bee Colony, Classification, Hybrid Prediction Model, Kernel Density Estimation, and Adaptive Self-Organizing Map Neural Network (MSOFMNN).

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## INTRODUCTION

The risk of cardiovascular disease is raised twice in those with type 2 diabetes [1]. Calculating CVD risk prior to initiating medication is recommended by guidelines for the management of type 2 diabetes [2-3]. While several CVD prediction models have been created throughout the years, only a

few have been tailored to persons with type 2 diabetes [4]. Relative insulin insufficiency leads to type-2 diabetes (T2D). Type 2 diabetics may still secrete insulin, but it may not work properly or they may not create enough insulin to adequately regulate their blood sugar levels [5].

Most cases of diabetes are due to T2D [6]. Diabetes' cardiovascular disease pathogenesis is multifaceted and not just attributable to hyperglycemia. Hypertension and dyslipidaemia are only two of the many risk factors that contribute to the onset of early CVD in people with Type 2 Diabetes Mellitus (T2DM). A common complication of type 2 diabetes is high blood pressure, which may speed up the onset of vascular disease. Small dense low-density lipoprotein (LDL) is modestly enhanced in people with diabetes, whereas high-density lipoprotein (HDL) levels and composition are decreased, and triglyceride-rich lipoprotein particles are increased. Reduced amounts of changed HDL are less able to engage in atheroprotective processes such reverse cholesterol transport, and glycated, tiny dense LDL is linked to increased oxidative stress inside the vasculature. Therefore, patients at high risk of CVD may be identified by early detection of insulin resistance and reduced endothelial function, allowing for targeted, intensive management of risk factors. Important characteristics in the dataset are not chosen, and unnecessary data in the T2D patient records are eliminated, which lowers the quality of the T2D patient prediction findings. The purpose of this research was to examine potential risk factors for cardiovascular disease in people with type 2 diabetes. The following are the most critical components of the planned works: Dimensionality reduction for initial data processing You may simplify your data by using the KLD - PCA approach, which is also utilised for dimensionality reduction. After data dimensionality reduction, KDE is used to examine CVD risk variables. The goal of this research is to provide a technique of prediction that makes use of SSL. To classify newly diagnosed patients into type 2 diabetes or not, a Hybrid Prediction Model was developed, with unsupervised IFCM accuracy and semisupervised MSOFMNN classification methods. This model was developed by first reducing the irrelevant or unimportant features in the type 2 diabetes patient records from the KDE similarity measurements results for CVD risk factors. In the proposed hybrid prediction model, the ABC-DE method is used to identify key characteristics from T2D patients' medical histories.

## **BACKGROUND STUDY**

Large volumes of data are created in today's medical field, but the gap between what can be learned from this data and how it may be put to use is growing. between accumulating information and making sense of it Having access to so much information makes it difficult to evaluate trends rationally. As a result, there is a rising need for smart data analysis, like data mining, to help provide information that physicians may use to make better judgments. Despite the overwhelming evidence of its efficacy, many nations restrict the prescription of cardiovascular risk reduction medication, with national recommendations recommending that patients have their risk of CVD evaluated to ensure therapy is focused to those at greatest absolute risk. The risk of cardiovascular disease in diabetics has been predicted using multivariate risk scores. In a meta-analysis of treatment trials found that the oral hypoglycemic medication rosiglitazone increased cardiovascular risk relative to other regimens or placebo. As opposed to focusing on individual patients, they looked at the whole experiment. The overall number of events was low, and there was no uniform technique for verifying them across trials. If a classification model could find these dangers in a clinical database, it would greatly improve its use and strengthen the body of evidence. The results of feature selection

and no feature selection may be compared with the help of classification algorithms.

### **PROPOSED METHODOLOGY**

The primary causes of morbidity and death in people with diabetes are increasingly cardiovascular problems. The prevalence and severity of cardiovascular disease in diabetic people has a tremendous and growing influence on public health. Early onset cardiovascular disease is associated with a number of risk factors in type 2 diabetes, including hypertension and dyslipidaemia. Since most existing classification or learning methods use a supervised or unsupervised learning, feature selection in T2D becomes challenging, and feature classification in T2D patients becomes a major important issue. However, no existing T2D classification methods support semi-supervised learning, which combines supervised and unsupervised learning to overcome the limitations of both. Important aspects of T2D patient records are identified using ABC-DE, and then the work focuses on the classification job or detection of T2D patient records with CVD risk factors. The primary goal of this proposed study is to use a hybrid semisupervised learning method based on an MSOFMNN prediction model to investigate the common clinical and behavioural characteristics that contribute to CVD risk among people with type 2 diabetes. Using KLD-PCA, where the weight values of the PCA are determined using the Kullback Leiber divergence, the suggested system preprocesses the T2D data with CVD risk and also performs dimensionality reduction.

Once the KDE has been used to assess risk variables for CVD, To improve the accuracy of predictions, a hybrid method is used to exclude less relevant characteristics from the data used for feature selection. In order to forecast T2D for CVD risk factors, we employ unsupervised classification using IFCM clustering algorithms on the features we've chosen and their estimated CVD factors. Following this, a semisupervised classification job is carried out, with MSOFMNN being used to predict the CVD risk of individuals with type 2 diabetes.

### **INFORMATION REGARDING DATASETS**

These are the characteristics of diabetes patients taken from actual medical records that make up the dataset: Body mass index (weight in kilogrammes divided by height in metres squared), plasma glucose concentration after 2 hours of an oral glucose tolerance test, diastolic blood pressure, triceps skin fold thickness, 2-hour serum insulin, and the number of times a woman has become pregnant are all variables that can be used to predict a person's risk of developing type 2 diabetes. Class variable age (in years), Age group (0 or 1). Body mass index (BMI), weight (kg), waist circumference (cm), systolic blood pressure (SBP) (mmHg), diastolic blood pressure (DBP) (mmHg), blood glucose (mg/dl), total cholesterol (mg/dl), high-density lipoprotein (HDL) cholesterol (mg/dl), low-density lipoprotein (LDL) cholesterol (mg/dl), and trig The risk of cardiovascular disease in people with type 2 diabetes may be analysed by altering the values of several variables (T2D). Treatment strategies for type 2 diabetes are heavily influenced by the difficulty of managing the many risk factors responsible for cardiovascular disease in this population. Kullback-Leibler Divergence and Principal Component Analysis for Preprocessing and Dimensionality Reduction (KLD-PCA)

The most crucial factor, as it determines how reliable the analysis' findings will be, is the accuracy and completeness of the data. Preprocessing data to enhance the reliability of mined data and the

productivity of the mining operation [7]. Preprocessing of T2D with CVD risk variables using KLD-PCA. Which eigenvector of the data has the biggest Eigen value? This eigenvector represents the most variation and is therefore the most crucial for the prediction process in principal component analysis. The data are filtered out and cleaned up during the preparation phase, according to this theory. A quick look at the numbers suggests that we may safely substitute 0 for any missing information. To get around PCA's main flaw—randomly produced weight values—we estimate them using KLD. Recommendation of KLD-PCA for preprocessing of T2D with CVD risk factor. Hospital data on people with type 2 diabetes, together with information on their CVD risk factors and t dimension, are included in dataset D. The KLD-PCA method isolates a region of the attribute value space whose basis vectors align with the maximum-variance axis of the original T2D data set. To illustrate this, let's say the linear T2D data space mapping that eliminates extraneous or missing attributes to create a new, lower-dimensional data set. Reducing the number of dimensions and the number of irrelevant data variables results in the equation (1), which displays the new reduced dimensional and reduced irrelevant data variable vectors (1). (2)

The eigenvector's eigenvalue and its corresponding covariance matrix are shown below. Each eigenvector's eigen value is used to rank it from highest to lowest. The biggest eigen value corresponds to the most significant variable and data vector that exhibits the largest variation. In order to choose the most relevant global variable and data vector from the available training samples, PCA uses all of the variables from the T2D patient's medical record that pertain to CVD risk factors. When there are more non-T2D data ones than T2D with CVD risk factor ones, PCA's effectiveness decreases. Using KLD techniques from principal component analysis, the weight transformation matrix is found in equation (1).

As a result, the significance of attribute, represented as  $I_n$  (3), denotes the total number of training examples, and denotes the number of instances with the value. The chance that the attribute's value is denoted by  $i$  in this formula is denoted by the symbol.

### **MEASURING ATTRIBUTABLE COSTS WITH KERNEL DENSITY ESTIMATES (KDE)**

Here, we use Kernel Density Estimation (KDE) for the prediction of T2D with CVD risk variables and assess the values of the characteristics for making such predictions. Take the highest value that meets all of the criteria for each characteristic. Body mass index (BMI), weight (kg), waist circumference (cm), systolic blood pressure (SBP) (mmHg), diastolic blood pressure (DBP) (mmHg), glucose (mg/dl), total cholesterol (mg/dl), high-density lipoprotein (HDL) cholesterol (mg/dl), low-density lipoprotein (LDL) cholesterol (mg/dl), and trigly Using percentages, we may compare HbA1c, Fibrinogen, and us-CRP levels. In order to build a new feature population for T2D samples, the DE algorithm makes use of a mutation operation as its starting operation, and a selection operation guides the feature selection process in the direction of CVD Risk factor evaluation or prediction. The DE method also employs a non-uniform crossover, which means that it is possible for the algorithm to preferentially adopt parameters for the children's feature vectors from some of the feature vectors associated with T2D patients whose medical histories include CVD risk factors. The recombination (crossover) operator effectively mixes up T2D patient feature information by employing present feature of T2D patient population members to generate trial vectors. At the outset of DE, all T2D patient data that includes CVD risk variables are used to

generate a random population of features of T2D patient's solution vectors using the ABC algorithm's employee bee phase. The feature selection solution for the T2D patient population with CVD risk factors is obtained based on the maximum number of bee cycles for each newly formed feature sample.

When looking for the best traits to use to identify T2D patients with CVD risk factors, the mutation operation broadens the search field. (7) where  $F$  is a scaling factor with values between zero and one; (8) where  $x$  and  $y$  are solution vectors selected at random; The parent feature vector of T2D patients with CVD risk factors is crossed with the mutant vector to create a trial vector (9): (9), where  $r$  is the crossing constant, is a real value between 0 and 1, and  $j$  is the index of the relevant array element. When using DE to establish patient characteristics for T2D, the fitness value from equation (15). Observational bees conduct worldwide research to learn about novel features of T2D patients and update worldwide optimal feature selection outcomes. Unknown to the hired bees, a scout bee has uncovered a new set of traits that may be utilised to better characterise T2D patients. The cycle of these three operations is repeated until the fulfilment of a termination requirement. Each attribute of T2D patients has a corresponding fitness value that is calculated using the fitness function. (10) Set equal to the value of the risk factor in equation (11). An artificial observing bee selects a feature solution for type 2 diabetic patients based on the probability value, which is determined by the following formula.

where  $n$  is the number of features chosen by the observer bees and  $f$  is the fitness value of the feature solution. In The ABC use the following equation to generate a potential food position from the previously stored one: where  $i$  and  $j$  are arbitrary indices and  $k$  is a random integer between  $1$  and  $n$ . A parameter may be adjusted to a valid feature selection value if the value it generates exceeds a threshold. In this work, if a parameter's value goes over the allowed range, the value goes back to the allowed range. When bees forsake nectar for a new food source, the scouts must make a similar decision. A feature is considered abandoned in ABC-DE if its position among the existing T2D patient features cannot be improved after a certain number of cycles. Let's pretend the deprecated source is  $f_{old}$  and the scout has found a fresh source of features to replace it. One possible definition of this process is (13) Each candidate's performance is compared to its previous one after the artificial bee has created and assessed the specified aspects of a T2D patient's location. If the newly-obtained nectar from feature selection of T2D patient data is as good as or better than the previous feature selection source, the latter is discarded and the former is stored instead. If the new one isn't learned, the old one stays in the mind. First algorithm: an optimization procedure based on the artificial bee colony -differential evolution (ABC-DE)

Step 1: Assign a starting number to each population of solutions.

Features

2) Conduct a population analysis

3. Repeat

4, a mathematical approach to mutation

Equational recombination, number five

Equational crossover, number six

Not until prerequisites are fulfilled, requirement no. 7

In a set, the cycle is always 1.

9. Repeat

Best feature selection solutions are created for the features used in the workplace and then evaluated. 10.

Eleven. Take the workers' bees' qualities into account through the greedy selection procedure.

Figure out the probabilities of the feature-solution combinations.

Construct the new feature options for the audience based on the chosen solutions and assess how effective they are.

### **For traits that are of interest to spectators, use a greedy selection procedure**

When the scout has reached a dead end with a feature, step 15 is to find the solution the scout had previously given up on and step 16 is to memorise the best solution that has been reached randomly.

17. 18. till IMPROVED Focus initially on confirming the selected classes using the unsupervised approaches, such as FUZZY C MEANS CLUSTERING (IFCM), before moving on to the use of the Classification algorithms. In this study, an IFCM clustering is used to verify the integrity of the cleaned-up dataset before using the clustering algorithm's class labelling functionality. In conventional FCM clustering approaches, distance measure is used to simply determine the degree to which two data points vary from one another. The worldwide context of the data is disregarded. However the density of data points in a cluster could be distinctly different from other clusters in a data set. To adjust the distance measure in the standard FCM, it is suggested to use a regulatory factor depending on cluster density. The regulator here makes use of the median result of an iteration process in addition to the form of the data set, setting it apart from previous methods. In addition, the regulatory factor makes real-time adjustments to the distance measure function until the predetermined goal is met. It is common practise to determine the density of points given a set of CVD risk factors for T2D with certain characteristics for each point as: (14) Where is the effective radius for density assessment. To adjust the distance metric, cluster density is used.

### **CONTENT-BASED CLASSIFICATION THROUGH PARTIALLY SUPERVISED LEARNING**

The reduced dimensionality data for classifying patients with type 2 diabetes in the KLD-PCA are then clustered according to their class labels, yes or no. The last step is to use the IFCM clustering's unsupervised class labels in a classification challenge. Results from ABC-DE are grouped and used as input for MSOFMNN's semi-supervised learning, which only needs a few identified patterns to provide useful predictions. Several methods have been used to compile the findings of CVD risk factors in T2D patients who have been labelled. The current method utilises ground-truth samples of T2D patient features labelled for both classes for experimental purposes. Different weight initializations are applied to the labelled and unlabeled neurons after the collection of labelled feature selection data. The weight vector for the  $j$ th output neuron, represented by, is initialised with the normalised feature values of the associated labelled pattern if the class label of the chosen T2D patients' characteristics is known, else it is initialised randomly between [0, 1]. The MSOFMNN is fed training samples from the input feature-selected clusters in a linear fashion. The dot product, between and, is determined as, at each iteration. (19)

At the beginning of the training phase, we exclusively use the labelled T2D patients with CVD risk

factors to make the following adjustments to the network's link weights. For a T2D patient with CVD risk factors, the weight vector of the output neuron is updated using Eq. (20) if the class label of the clustered features samples is known (20) where signifies the rate of improvement in the  $i$ th iteration of learning, and it decreases with anything which is growing faster than expected. To begin with, the winning neuron and its surrounding neurons' weight vectors are initially far from the input clustered T2D features samples under consideration. The convergence  $O$  for each iteration 'of learning labelled clustered T2D features is determined by the following formula: (21) where is a cutoff value established for T2D patients' CVD risk factors. As long as the difference between the outputs of two successive iterations is smaller than, where is a modest positive amount, weight updates are performed [7]. So that the dot product is always between 0 and 1, we normalise the weight vector's components as follows: (22) The network is then provided with unlabeled clusters of T2D feature patient data at the end of each training phase, and the soft class labels are computed using the idea of fuzzy set theory. Consider two fuzzy sets, one for the class of modified CVD risk factors and the other for the class of unmodified risk factors. Patients with type 2 diabetes who have their data clustered without labels may have their membership values for the CVD risk factor class and the unaltered CVD risk factor class calculated. Each unlabeled sample is assigned a probability that falls into one of two categories: either the CVD risk factor class that has undergone a change or the CVD risk factor class that has remained intact. Let the value of membership in the unlabeled cluster sample be denoted by and the values of membership in the CVD risk factor class and the unmodified CVD risk factor class by and, respectively. It is possible to derive these numbers by using the formulas: [8] Once the target CVD risk factors categorization findings are determined, they are updated in the same manner using the K-nearest neighbour approach. Each clustered feature sample from a T2D patient without labels has its K closest neighbours calculated. Rather of considering all clustered feature chosen samples, just a limited number of cluster samples inside a window surrounding that unlabeled categorization sample for CVD risk variables in T2D patients should be included in the search for the K number of closest neighbours[9]. Results from the estimated classification of the target CVD risk variables are given by (24) Training the network and re-estimating soft class labels of the unlabeled clustered T2D features patient's data using Eqs. We keep repeating steps (28) and (29) until we reach a point when the network is holding steady. Sum of squared errors,, calculated after each training iteration as: (25) When the error between two training stages is less than, the learning process stops (where is a small positive quantity). Below is a representation in algorithm form of the suggested semi supervised learning approach: Type 2 diabetes patients with cardiovascular disease risk factors are classified using a semi-supervised MSOFMNN learning algorithm First, from the cluster reference map, collect a few labelled samples.

Second, we'll set the MSOFMNN's connection weights to zero. Each cluster's feature samples that have been identified may be used to establish the weights of the output neuron that represents that cluster. Random weights in the range [0, 1] are assigned as the starting point for the output neurons that represent the unlabeled cluster feature samples. Third, using just the labelled cluster feature data, revise the network weight vector for the output neuron corresponding to each of the unlabeled cluster feature samples. Fourth, run the unlabeled cluster feature samples through the network using a similarity measure ( $d$ ) and a specified threshold value ( $\theta$ ) to get their membership value[10].

if in the class of CVD risk factors that have increased, then  $= \max[d, (1 - d)]$ . if in the class of CVD

risk factors that have decreased, then  $= \min[d, (1 - d)]$ .

In all other cases, the class of CVD risk factors that have undergone a change is represented by  $\min[d, (1 - d)]$ , whereas the class of CVD risk factors that have remained stable is represented by  $\max[d, (1 - d)]$ . Step 5: Use the membership values of the K closest neighbours to assign the target value to each unlabeled cluster feature sample. In Step 6, unlabeled cluster feature samples are chosen for further training if the estimated goal value in the class of modified CVD risk factors is higher than that of the class of unmodified CVD risk factors. Seventh, include both the labelled and chosen unlabeled cluster feature samples into the network weight vector for the output neuron corresponding to each unlabeled cluster feature sample [11]. Eighthly, until convergence is reached, repeat steps 4, 5, 6, and 7. Continue to Step 9 after convergence has been reached. The ninth step is to give each of the unlabeled patterns a strict classification label.

### **EFFECTS OF THE EXPERIMENTS**

Data were not acquired with the intent of using them in a study. From 2000 to 2004, UCHT included the collection of diabetes patients' data in a clinical information system as part of normal patient treatment. For 3857 individuals, the database comprised physiological and laboratory data, each of which was characterised by 410 characteristics. Patients with type 1, type 2, and various forms of diabetes, such as gestational diabetes, were all represented. It's necessary to institute a system for judging performance. Accuracy, defined as the proportion of correctly labelled examples relative to the total number of instances, is a popular metric in the literature. Classifications that are true positives (TP) and true negatives (TN) are accurate. Incorrectly predicting a positive result when it is really negative is called a false positive (FP) (negative). To make a false negative (FN) prediction is to falsely state that the result is not yes when it is, in fact, yes. Accuracy, specificity, and sensitivity were calculated using Eqs. (26), (27), and (28), respectively, in this investigation (28) (26) (27) (28)

Accuracy, sensitivity, and specificity may all be measured using these indicators. The percentage of positive tuples that are properly recognised is known as the sensitivity, whereas the proportion of negative tuples that are correctly identified is known as the specificity.

This study proposes an unique unsupervised learning and semi-supervised when compared to current prediction approaches; the suggested work uses a KDE-based similarity assessment to evaluate the significance of individual characteristics. The proposed ABC-DE-IFCM- MSOFMNN based prediction methods achieve higher Sensitivity than the existing classification methods like PSO-IFCM-ELM, IFCM-SVM, and K-C4.5. This is because the feature selection (ABC-DE) is performed after the preprocessing and dimensionality reduction methods, and the KDE based similarity measure. The suggested work also uses MSOFMNN for semisupervised learning, which improves prediction accuracy. However, the suggested ABC-DE-IFCM- MSOFMNN based prediction techniques achieve lower specificity than the current classification methods like SVM and k-nearest neighbours. The specificity of the PSO-IFCM-ELM, IFCM-SVM, and K-C4.5 prediction systems, while the proposed ABC-DE-IFCM-MSOFMNN system has lower specificity. This is because in the proposed work, feature selection (ABC-DE) is performed only after the preprocessing and dimensionality reduction methods have been completed, and KDE-based attribute



similarity measurement is performed to improve prediction accuracy.

## **CONCLUSION AND FUTURE WORK**

Type 2 diabetics are at an elevated risk for developing cardiovascular disease (CVD), which is a potentially fatal consequence of the condition that imposes a heavy economic and human toll. In order to provide high-quality treatment for people with diabetes, it is essential to first identify those at high risk of cardiovascular problems and then focus on modifiable variables significantly related with CVD risk. The prediction accuracy suffers while trying to identify the most relevant variables in patients with type 2 diabetes and CVD risk factors. This study proposes a unique semisupervised MSOFMNN classifier for predicting CVD risk variables in T2D patients, which might help alleviate these issues. After performing KLD-PCA preprocessing and dimensionality reduction, assessing the impact of CVD risk factors using KDE methods, selecting features using ABC-DE, proposing IFCM clustering algorithm for unsupervised learning, and finally discussing MSOFMNN to perform prediction of T2D with CVD risk factors, the paper concludes with a discussion of future work. For the first iteration of the network, only a small number of annotated T2D patients are used. Fuzzy set theory is then used to each unlabeled data sample from T2D patients to establish membership values, in both groups. The membership values of the K closest neighbours are then used to estimate the soft class label for each of the unlabeled T2D feature chosen patients' data. Moreover, classification parameters are used to provide a statistical validation of the experimental outcomes. When compared to other approaches, the suggested strategy performed well. There is still a lack of clarity on the intricate interplay between diabetes-related medical expenditures, patient demographics, and the prevalence of co-morbidities. This investigation starts the process of untangling these connections and adds additional data to the growing body of knowledge concerning cardiovascular disease's outsized and singular effect on diabetic medical care expenditures. In order to better understand the correlation between age at diabetes diagnosis and CVD, further studies should compare participants diagnosed with diabetes at younger and older ages.

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