

A Theoretical Evaluation of Mellitus Diabetes using Data Mining and Machine Learning

Shivani Patel¹, Sanjay Chaudhary², Prakashsingh Tanwar³

¹Research Scholar, Computer Science and Information Technology, Madhav University, Pindwara (Sirohi) Rajasthan, India
²Research Supervisor, Computer Science and Information Technology, Madhav University, Pindwara (Sirohi) Rajasthan, India
India

³Computer Science and Information Technology, Madhav University, Madhav University, Pindwara (Sirohi) Rajasthan, India

ABSTRACT

Pattern identification, processing, and treatment are all common uses of data mining techniques in medical diagnostics. Diabetes is a metabolic illness in which elevated blood sugar levels persist for an extended period of time. Diabetes mellitus (DM) is a collection of metabolic illnesses that puts a lot of pressure on people all over the world. According to these studies, India accounts for 19% of the world's residents. Category 1 and Category 2 diabetes are covered in this overview. Theoretical basis is used to compare previous researcher methodologies and processes. To process datasets, the Weka open-source tool is employed. In the first half, we'll talk about gathering data from various medical departments; in the second part, we'll talk about data cleaning and then algorithms for removing noisy data. Also, several Algorithms were used to determine the best characteristic. Finally, we'll look at alternative machine learners for diabetes data classification and discuss future research directions.

Keywords : Theoretical, Evaluation, dataset, Pre-Process, and machine learning

I. INTRODUCTION

In healthcare, computer-based assistance is becoming increasingly important. There are few other domains that have as many inventive innovations with such a large social impact. There is a long history of computer-based decision support in medicine, dealing with complicated challenges such as disease diagnosis, administrative decisions, and assisting in the prescription of suitable therapy. Diabetes, an incurable chronic disease, is one of the useful applications in medicine. It is a set of metabolic illnesses in which the blood sugar levels of a person are unusually high, either because the body does not create enough insulin or because the insulin produced does not reach the cells.

For most businesses, data and information have become key assets. In the process of uncovering knowledge in medical databases, data mining is a crucial step. Databases are collections of information having a specified structure and function. The programmes that create and manipulate these data are known as database management systems, or DBMS. The total process of extracting knowledge from data is known as knowledge discovery in mining is the databases. Data process of computationally extracting latent knowledge

structures expressed in models and patterns from large data sets.

Type 1 diabetes, type 2 diabetes, and type 3 diabetes are the three types of diabetes. Insulindependent diabetes, often known as type 1 diabetes, is an autoimmune illness in which the body attacks its own pancreas (typically starting in childhood). The wounded pancreas can no longer make insulin.

Non-insulin-dependent diabetes, often known as type 2 diabetes, is the most common kind of diabetes in adults, accounting for almost all cases. Type 2 diabetes is a milder form of diabetes that normally occurs later in life, however because of the obesity and overweight epidemic in childhood, more teenagers are developing type 2. In persons with type 2 diabetes, the pancreas produces some insulin. However, either the amount produced is inadequate to suit the demands of the body, or the body's cells are resistant to it. Insulin resistance is most common in adipose, liver, and muscle cells, making the pancreas work too hard to produce enough insulin. Obese persons have a higher risk of developing diabetes.

Diabetes that develops as a result of pregnancy is known as gestational diabetes. Insulin resistance affects between 2% and 10% of all pregnancies. Because a mother's high blood sugar levels are transmitted down to her baby through the placenta, they must be maintained under control in order to defend the babe's growing and expansion.

II. Literature Study

Loannis et al. [6] used SVM, LR, and NB to predict different/various medical datasets, including diabetes datasets, utilising 5 fold cross validation. Based on their findings, the researchers assess the accuracy and performance of the algorithms and conclude that SVM delivers the superior accuracy over the other technique.

Francesco et al. [7] invented the multilayer perceptron, random forest, and Decision Tree machine learning algorithms for prediction. According to the researchers, multilayer perceptron (MP) provides excellent accuracy.

Kandhasamy and Balamurali [8] used the Artificial Neural Networks, K-Nearest Neighbour, Navier Bayes, and J48 classification methods. In this study, the Nave Bayes algorithm provides greater accuracy in the diabetes dataset. In additional datasets on their research, the two algorithms KNN and ANN give great accuracy.

Different data mining strategies were developed by Meng et al. [9] to forecast diabetes illnesses. Three approaches are used in this: ANN, LR, and j48. The results show that the j48 machine learning approach has a higher level of accuracy.

Zhang et al. [10] used Nave Bayes Random Forest and Adaboost to train machine learning approaches to predict diabetes illnesses. Random forest outperformed other models, according to the researchers.

J48, multilayer perceptron, and Random Forest are used by Francesco et al. [11]. In compared to the others, j48 provided superior accuracy (77.5%).

On many datasets, including diabetes, Rani and Jyothi [12] employed Nave Bayes and ANN. With an accuracy rating of 77.01 percent, Nave Bayes exhibited great accuracy. Saravananathana and Velmurugan [13] employed CART, SVM, and K-NN among other machine learning techniques. According to their research, CART has a 62.28 percent accuracy, SVM has a 65.04 percent accuracy, and K-NN has a 53.39 percent accuracy.

To assess whether or not a person is diabetic, Yasodha and Kannan [14] applied machine learning classifiers to a range of datasets. The data was categorised using WEKA, and the data was analysed using a 5-fold cross validation approach, which works well on small datasets, and the findings were compared in this study. naive Bayes, J48, REP Tree, and Random Tree are among the algorithms employed. With a 60.2 percent accuracy rate, J48 was judged to be the most efficient. By analysing and analysing data patterns via classification analysis using Decision Tree and Nave Bayes algorithms, Sumbaly et al. [15] created diabetes detection systems. In comparison to Naive Bayes, the experimental findings demonstrate that the j48 algorithm has a 74.8 percent accuracy rate.

Gupta et al. [16] attempted to evaluate and analyse the outcomes of multiple classification techniques in WEKA, as well as identify and quantify the accuracy, sensitivity, and specificity percentages of various classification methods. The results suggest that Random Forest has the highest accuracy of 81.3 percent, 59.7% sensitivity, and 81.4 percent specificity.

Chikh et al. [17] used an enlarged Artificial Immune Recognition System 2 (AIRS2) termed modified Artificial Immune Recognition System 2 to increase the identification accuracy of diabetes diseases (MAIRS2). The K-nearest neighbour approach is replaced with fuzzy K-nearest neighbours to increase the diagnosis accuracy of diabetes diseases. The authors were able to strike a good balance between data reduction and classification accuracy. The suggested system (MAIRS2) fared better than the AIRS2 benchmark. The authors were able to get the highest classification accuracy of 80.10 percent by utilising MAIRS2.

Sharmila and Manickam [18] set out to analyse data in order to predict diabetes from patient medical records. This work uses the R tool to analyse diabetes from large medical data using the decision trees technique. The decision tree algorithm has a 79.33 percent accuracy.

In order to anticipate the most frequent kinds of diabetes, as well as related complications and therapies, Lavanya et al. [19] concentrated on constructing a prediction model by studying the strategy in a Hadoop/Map Reduce context. The proposed predictive analysis system design includes data collection, warehousing, predictive analysis, and the processing of analysed results.

Tiwari and Diwan [20] have presented a method for identifying cancer sickness patterns that is both automated and hidden. In the offered system, data mining techniques such as association rules and clustering were used. A major job in this work is attribute-based clustering for feature selection. This method was used to vertically split the data collection. The data is divided into two clusters, one including all significant properties and the other containing all irrelevant ones.

Khaleel et al. [21] focused on data mining approaches that are critical for medical data mining, namely for detecting common illnesses including heart disease, lung cancer, and breast cancer. Some of the data mining algorithms utilised on medical data include apriori and FPGrowth, as well as unsupervised neural networks, linear programming, and association rule mining. The association rule mining approach locates elements in a collection that appear frequently. Medical mining gives the data needed to make educated diagnosis and decisions.

Chaurasia and Pal [22] forecasted diabetic illnesses using several machine learning techniques. WEKA, an information retrieval programme with a collection of machine learning techniques, is utilised. This inquiry employs Naive bayes, j48, and bagging. j48 has an accuracy of 84.35 percent. Bagging achieves an accuracy of 85.03 percent. On this dataset, bagging provides a superior classification factor.

Parthiban and Srivatsa [23] published a study on detecting coronary artery disease in diabetic individuals. Machine learning techniques were used to do this. WEKA employs the Naive Bayes and SVM algorithms. Using SVM, the greatest accuracy of 94.60 is attained.

Sumbaly et al. [24] used two approaches to predict diabetic complications: decision trees and Naive Bayes. j48 performed Cross Validation and Percentage Split (PS) independently. Using PS, Naive Bayes provides 79.5652 percent accuracy. Using rate split test, algorithms provide the highest level of accuracy. Alic et al. [25] compared artificial neural networks (ANN) and Bayesian networks, the two most widely used sickness prediction methods. Because of the independent association between observed nodes, Artificial Neural Networks achieve a higher accuracy of 89.78 percent compared to Bayesian Networks' 80.43 percent.

To predict liver illness, Murthy et al. [26] employed support vector machine (SVM) and Nave Bayesian Classification techniques. This data collection contains 560 occurrences as well as 10 attributes. The comparison is based on precision and execution time. Bayes Classifier yields 61.28 percent accuracy in 1670 milliseconds. In 3210 milliseconds, SVM achieves 79.66 percent accuracy. SVM has the greatest accuracy when compared to the Nave Bayesian for predicting liver illness. The Navies Bayesian algorithm takes less time to run than the SVM method.

Baby and Vital [27] built a prototypical that can envisage the sympathetic of renal disease based on a data collection of people with kidney illness. The model examined the outcomes of numerous classification techniques, including random forests, Decision Trees, j48, and K-means algorithms, and found that RF outperformed the others.

Using machine learning approaches, Razia and Rao [28] created a framework model to identify thyroid illness. Unsupervised and supervised learning are employed to identify thyroid disease, and the framework model beats the decision tree model.

Alehegn et al. [29] employed SVM, Nave Net, Decision Stump, and the Proposed Ensemble technique to forecast diabetic diseases. The suggested ensemble technique has a 90.36 percent accuracy. In comparison to others.

The Adaboost M1 method was combined with a random committee by Kang et al. [30]. The accuracy of the prediction is 81.0 percent.

III. Methodology

The process of collecting knowledge from data using computer-based technologies is known as data mining. Data collection and preparation are the first steps in the strategy used to complete the research assignment. The Pima Indians Diabetes Database, which was gathered from several archives, served as the training dataset for data mining. The data preparation process covered all operations needed to create the final dataset from the raw data. Different modelling methodologies are chosen and used, with their parameters adjusted to provide the best results. To tackle the same data mining problem, classification algorithm techniques are employed.

Dataset

The data was gathered from Chinese hospital physical examination records. This data is split into two categories: healthy persons and diabetics. Data from two healthy people's physical examinations are available. As the training set, we used 164431 instances of data from healthy people's physical examinations. In the alternative data set, 13700 samples were picked at random as an independent test set. The 14 clinical assessment indexes include age, pulse rate, breath, left systolic pressure, right systolic pressure, left diastolic pressure, right diastolic pressure, height, weight, physique index, fasting glucose, waistline, low density lipoprotein, and highdensity lipoprotein.

Another piece of data is on diabetic Pima Indians. All of the patients, in particular, are Pima Indian women over the age of 21. The dataset includes information on the time of pregnancy, plasma glucose concentration after a 2-hour oral glucose tolerance test, diastolic blood pressure, triceps skin fold thickness, 2-hour serum insulin, BMI, diabetes pedigree function, and age. After missing data is eliminated, this dataset's 786 diabetes records are reduced to 92.

Pre-Process

- **Cleaning the data:** Many portions of the data may be meaningless or missing. In order to control this component, data purification is performed. It requires coping with data that is missing, noisy, and so on.
- Data Reduction: Data mining is a technique for dealing with massive volumes of information. Analyzing big volumes of data gets increasingly complex. To eliminate this, we use a data reduction technique. Its objective is to increase storage efficiency while minimising data storage and analysis costs. The four phases in the data cube aggregation method are data cube aggregation, attribute subset selection. numerosity dimensionality reduction. and reduction.
- Data Transformation: In this stage, the data is transformed into a format that can be used in the mining process. This can be done in a variety of ways: 1. Consolidation 2. Attribute Selection 4. Creation of a Concept Hierarchy 3. Disambiguation.

Feature Selection Methods

Subset of features In the data mining process, selection is a strategy for data reduction. Data reduction decreases the amount of data so that it may be utilised more efficiently for analysis.

- Need of Attribute Subset Selection: There might be a lot of characteristics in the data collection. However, some of those characteristics may **be** obsolete or outdated. The purpose of attribute subset selection is to discover the smallest possible collection of characteristics such that removing those that aren't useful has little impact on the data's value and the cost of data analysis may be lowered. The found pattern is also easier to grasp when mining on a smaller data set.
- **Process of Attribute Subset Selection:** The brute force technique, in which each subset (2n potential subsets) of the data with n

characteristics is analysed, can be exceedingly costly. The best technique to complete the work is to apply statistical significance tests to identify the greatest (or worse) features. The statistical significance test implies that the qualities are unrelated. This is a greedy technique in which a significance level is chosen (the statistically optimal value for a significance level is 5%), and the models are tested repeatedly until the p-value (probability value) of all characteristics is less than or equal to the significance level chosen. Attributes with a p-value greater than the significance threshold are removed. This technique is continued until all of the attributes in the data set have a p-value that is less than or equal to the significance threshold. As a result, we have a smaller data set with no extraneous properties.

Machine Learning

- Support Vector Machine: The SVM classifier's goal is to locate the optimal hyperplane from which to divide the classification model. A extracted features and a class label are used to describe each trained model. The hyper-plane is trained and equipped to distinguish the majority of samples out of the same class from all the other samples. A binary classifier is what an SVM is. The logical concept(s) utilised for picture annotation are the classifier's output. The goal is to create a separating hyperplane that splits the collection of instances thus all locations of the same description are all on the same side of it.
- Naive Bayes: The Nave Bayesian method is among the most efficient and productive inductive learning approaches for machine learning techniques. The Bayes principle of likelihood function is involved. It presume that a class's properties are autonomous of one another. In other terms, it believes that the influence of a specific class's feature values is unaffected by the values of those other features. This is one of the

most well-known classification methods. This is most commonly utilised in the estimate of probability that correspond to a certain group.

Decision tree: The decision tree, which starts . with a single node representing the training samples, employs the tree structure. If all of the samples belong to the same class, the node is transformed into a leaf, and the class is used to identify it. Otherwise, the algorithm selects the discriminating attribute as the current node in the decision tree. The training samples are divided into several subsets, each of which generates a branch based on the value of the current decision node attribute, and there are several values that generate numerous branches. The preceding phases are repeated for each subset or branch gained in the previous step, recursively building a decision tree on each of the partitioned samples.

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K-nearest neighbour (k-NN): It's a type of machine learning technique that uses the input's nearest neighbors to categories it. It's an algorithm that keeps track of all instances and categorizes new ones using a similarity metric. It's also known as case-based reasoning. ii) the number of nearest neighbors iv) Slow learning KNN calculations have been used in a variety of applications, including statistical estimation and pattern recognition. KNN is a non-parametric order method that may be classified into two types: structure-based NN techniques and structureless NN approaches. All of the data in structure-free NN techniques is categorized into training and test data. The distance between the training and sample locations is calculated, and the nearest neighbor has the least distance. N uses information structures such the orthogonal structure tree (OST), ball tree, k-d tree, closest future line, axis tree, and focus line. When all characteristics are continuous, the closest neighbor arrangement is utilized. In two phases, a simple computation of the K nearest neighbor is performed: 1. Locate the training K cases that are the most similar to the unknown instance. 2. For these K examples, choose the most common categorization.

- Random Forest: A random tree number of co classifier contains a number of branches, each of which has been randomly grown. Iterations of the subsequent probability across picture classes are used to identify the nodes from each node. Each grid cell has a test that divides the region of data to be categorized in the most efficient way. Through transmitting an information down every node and summing the limb patterns attained, a picture is categorized. Variation may be introduced throughout learning at 2 places: when subsampling the training data so that each tree is created using a different subset, and when picking the node tests.
- Neural Network: A neural net is a supervised classification system that is fashioned after neurons, as the title suggests. The algorithm's determination is toward custom a extrapolative model to assign each input to one of several predetermined output classes. Whenever input data move through a succession of bunches of activating cells, the functioning in a neural net takes place. Levels are the terms used to describe these groups of batches. A layer of activation units receives the preceding layer's results as inputs everything at the same time to deliver output which are then handed onto next level. This procedure is repeated till the last layer produces the final total estimates.
- Ad boost: Ad boost is a machine learning metaalgorithm. In the binary classification task, ad boost is utilized. It is also a boosting algorithm. It is a fundamental algorithm for comprehending boosting. It may be utilized to improve the performance of the algorithms. It works well with slow learners.

Theoritical Evaluation

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This section will go through the many types of machine learners, as well as their benefits and drawbacks. Finally, a comparison classifier evaluation will be performed, based on training speed, accuracy, problem type, prediction speed, and performance.

TABLE I. COMPARATIVE ANALYSIS

Method Adva	intage	Limitation		
Support -SVM	A is a simpler	-SVM is a		
Vector algor	rithm.	binary classifier		
Machine -Crea	ate extremely	that may be		
[2,3,7,11] accu	rate	used to do		
class	ifiers.	multiclass		
-Less	over-fitting.	classification		
-Noi	se-resistant.	using pair-wise		
		classifications.		
KNN -Stat	ole in the	-It's		
[12,15,18,21] prese	ence of noisy	computationally		
train	ing data	costly, thus it's		
-Effe	ctive in the	sluggish.		
prese	ence of big			
train	ing data			
Decision -It	eliminates	-It's unclear the		
Tree over	fitting and	sort of distance		
[6,8,30,32] hence	e improves	to employ and		
accu	racy.	which attribute		
-Easy	y to use	to use in		
-Wo	rks with a	distance-based		
wide	range of data	learning to get		
-Mu	lti-	the greatest		
class	ification	results.		
assist	ance			
Random -Flex	tibly integrate	-The cost of		
Forest missi	ing data from	computation is		
[18,19,26] earlie	er nodes of	rather		
the t	ree.	significant.		
-Effi	cient on huge			

Naiver Bayes		-Easy to use.			-If		the
[24,26,28]		-Only a minimal			dependent		
		quar	ntity	of	varial	oles in	the
		train	ing da	ata is	mode	1	are
		requ	ired to j	predict	linearly		
		the test data.			connected, it		
					may		not
					funct	ion. As	s a
					result	, anot	her
					strategy must be		
					used to		
					elimi	nate	the
					associ	ated	
				variable.			
]	FABLE I	I.	CLASSIE	ier Eva	LUATIO	DN	
Fonturo							
reature	Naïve	sv	Decisio	Rando	K-NN	Neural	Ada
reature	Naïve Bayes	SV M	Decisio n Tree	Rando m	K-NN	Neural Netwo	Ada boo
reature	Naïve Bayes	SV M	Decisio n Tree	Rando m Forest	K-NN	Neural Netwo rk	Ada boo st
Training	Naïve Bayes Very	SV M Fast	Decisio n Tree Fast	Rando m Forest Slow	K-NN Fast	Neural Netwo rk Slow	Ada boo st Fast
Training Speed	Naïve Bayes Very fast	SV M Fast	Decisio n Tree Fast	Rando m Forest Slow	K-NN Fast	Neural Netwo rk Slow	Ada boo st Fast
Training Speed Accuracy	Naïve Bayes Very fast High	SV M Fast Hig	Decisio n Tree Fast Low	Rando m Forest Slow Low	K-NN Fast Low	Neural Netwo rk Slow High	Ada boo st Fast Hig
Training Speed Accuracy	Naïve Bayes Very fast High	SV M Fast Hig h	Decisio n Tree Fast Low	Rando m Forest Slow Low	K-NN Fast Low	Neural Netwo rk Slow High	Ada boo st Fast Hig h
Training Speed Accuracy Problem	Naïve Bayes Very fast High Classi	SV M Fast Hig h Eith	Decisio n Tree Fast Low Either	Rando m Forest Slow Low Either	K-NN Fast Low Either	Neural Netwo rk Slow High Either	Ada boo st Fast Hig h Eith
Training Speed Accuracy Problem Type	Naïve Bayes Very fast High Classi fy	SV M Fast Hig h Eith er	Decisio n Tree Fast Low Either	Rando m Forest Slow Low Either	K-NN Fast Low Either	Neural Netwo rk Slow High Either	Ada boo st Fast Hig h Eith er
Training Speed Accuracy Problem Type Prediction	Naive Bayes Very fast High Classi fy Fast	SV M Fast Hig h Eith er Fast	Decisio n Tree Fast Low Either Fast	Rando m Forest Slow Low Either Moder	K-NN Fast Low Either Depen	Neural Netwo rk Slow High Either Slow	Ada boo st Fast Hig h Eith er Fast
Training Speed Accuracy Problem Type Prediction Speed	Naive Bayes Very fast High Classi fy Fast	SV M Fast Hig h Eith er Fast	Decisio n Tree Fast Low Either Fast	Rando m Forest Slow Low Either Moder ate	K-NN Fast Low Either Depen d	Neural Netwo rk Slow High Either Slow	Ada boo st Fast Hig h Eith er Fast
Training Speed Accuracy Problem Type Prediction Speed Performan	Naïve Bayes Very fast High Classi fy Fast Yes	SV M Fast Hig h Eith er Fast Yes	Decisio n Tree Fast Low Either Fast No	Rando m Forest Slow Low Either Moder ate No	K-NN Fast Low Either Depen d No	Neural Netwo rk Slow High Either Slow	Ada boo st Fast Hig h Eith er Fast No

IV. Conclusion and Future idea

Some of the cases of diabetes in China and Pima Indians were included in the comparative study. The datasets were then subjected to the multiple imputation and listwise methods. After that, the performance of various system algorithms was compared to the performance of the system described in the associated study. We discovered that the performance of is influenced by feature selection and machine learning. If an ensemble-based classifier, such as the additional tree classifier, is utilized to optimize the performance parameters, this will be a future study path.

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