AN EFFICIENT HYBRID ALGORITHM FOR DIABETIC ANALYSIS WITH INTEGRATED FEATURES USING MACHINE LEARNING TECHNIQUES

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ABSTRACT

Recently diabetic problems are faced by the human irrespective of the age group which leads to the health issue, so it will be handled carefully through medicine. Existing system provides the support for controlling the diabetics through manual and automated testing tools and applications. These models are restricted to specific features based on the type of test conducted by the physicians. The broader level of features and its attributes are analyzed with a reliable model. The generic model with various hyper parameters is used in order to improve the accuracy. Outliers in the data sets are analyzed with suitable data sampling methods. There are various parameters considered for the experiments namely Hypertension, hyperlipidemia, blood sugar range and required insulin etc. The main objective of the proposed algorithm is to classify and predict the diabetes condition with high level of accuracy. The accuracy of the current algorithm is better when compared to existing supervised learning models with maximum reliability

KEYWORDS: ***Diabetic Analysis, Classification, Outliers, Hypertension, Hyperlipidemia, Data Mining***

1. INTRODUCTION

Diabetes disease occurs due to high levels of blood sugar (i.e. glucose) which affects the energy and insulin level. This mainly depends on food which is obtained by the human. Various risk factors exist in the diabetes patients namely obesity, lifestyle, family medical history, hypertension, high cholesterol level and so on. Diabetes is classified into type1 and type2 based on the level of sugar present in the human body. The symptoms of these diabetes includes excess urine level, thirst, reduction of weight, skin issues etc. Doctors suggested that the prediabetes is borderline diabetes with sugar level which ranges from 100 mg/dL to 125 mg/dL (i.e. milligrams per deciliter). The reading is taken during the blood sugar test in two types: fasting and post meal (PP). Figure 1 and Figure 2 shows that the hypertension and hyperlipidemia of the human. Type 2 diabetes is assessed based on the relationship between protein and mass distribution with fat. This method analyzes various parameters with people but it suffers the HbA1c and Glucose variability parameter, so it is done by using multiple regression based analysis for prediction [1]. Different examinations have been advised for pregnant women because the sugar level goes abnormal in recent years. Mobile based assessment is used to avoid the illness and emergency condition. This model identifies the diabetes in early stages which gives precautionary measures [2].

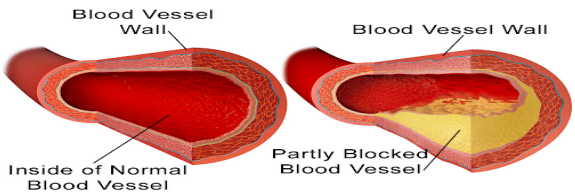

Figure 1.Hypertension

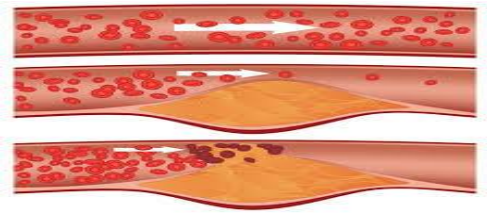

Figure 2. Hyperlipidemia

Type 1 diabetes goes in normal condition after taking a meal by the person. The calculation of insulin dose can be monitored using a decision support system which is done by implementing smart watches. It gives the information about the current sugar level through the display in the device [3]. The analysis of pathogenesis related to diabetes is carried out by identifying the target with clinical measurement. The diabetes treatment requires the hyper elements with their relationships namely genes, proteins etc. this method supports all kinds of diabetes treatment and drug management [4]. Type 1 and type 2 diabetes identified based on the insufficient supply and ability of insulin respectively. The diabetes patients freely post and share their experience over the social media with health related information. The model used to handle this information and predict the further data using machine learning approach [5]. Ensemble is a machine learning model which classifies the diabetic data either person having diabetic or not through prediction. It uses the binary classification with a high level of datasets using python packages. It uses chatbot based analysis including habits of lifestyle and eating with medical history [6]. Many people use social media for self-assessment and management of their health condition especially diabetes. There are various online sources available in the social networking platform namely analytical tools, gamification, zigbee devices based analysis and so on [7]. Diabetes management process is so costly because of high end wireless devices used for monitoring and testing by physicians. This is reduced by using cloud based systems using smart devices and the internet in ubiquitous manner [8]. Recently the diabetes disease has affected about 90% of the adult age persons, so it will be handled using black box based model. This model also gives inadequate results which overcomes the rule based approach. ERCT is a covering based technique with a scalable and accurate manner. It achieves about 85% of accuracy in cross validation method [9]. Smart diabetes diagnosis is done by using advanced machine learning models with patient

records in an accurate manner. Genetic algorithm with a fuzzy classifier is used to classify the data with 83% of accuracy. It also uses a reduced feature set with 70-30 train and test ratio [10]. The sentiment based network is designed by the data scientist and given to the support of physicians during diabetic treatment. It uses a multidimensional view of the features in patient medical record [11]. Neuro-fuzzy model is used for classification of diabetic patients with feature vector fuzzy rules. This model achieves 84% accuracy of analysis with minimum rules [12]. Diabetes deafness data sets are divided as a group namely treatment and control. The improvement ratio after treatment of control and treatment group is 29 % and 31 % respectively [13]. The existing models and techniques provide the support to the physicians for handling the diabetic patients with limited features or specific features. The specific features are always provided with accuracy but the other causes are never considered, so it will be analyzed with generalized attributes with high level features over different age groups of patients. The outliers are also analyzed with the root cause of the diabetic in various dimensions. The main objective of the proposed algorithm is to predict the diabetic disease of various age populations with the consideration of features like hypertension, hyperlipidemia, sugar level and insulin requirement level for achieving accuracy in an optimal manner.

2. **PROPOSED MODEL FOR HYBRID ALGORITHM**

Diabetics is a severe disease which causes the problem in human day to day life, so it will be controlled by following proper instruction given by the doctors. The proposed algorithm provides the support to classify and predicts the patients based on their diabetic level with various dimensions and properties. Table 1 represents the features of proposed analysis. The data are preprocessed by removing the noisy data, irrelevant information and null values etc. These data are analyzed in

Table 1. Diabetic features for analysis [14] [15]

Features	**Abbreviation**
chol	Total Cholesterol
stab.glu	Stabilized Glucose
hdl	High Density Lipoprotein
ratio	Cholesterol/HDL Ratio
glyhb	Glycosolated Hemoglobin
location	location and its level
age	age in years
gender	male/female
height	height in inches
weight	weight in pounds
frame	level factor
waist	waist in inches
hip	hip in inches

hypertension based and hyperlipidemia based. The parallel analysis is carried out achieving better accuracy. The relevant features are selected and removing useless from the data set. Outliers are detected from the selected features and perform the elimination process which means that this type of data affect the performance of the model. The parameters of the parallel analysis are generalized to make the broader attributes in order to create a robust model with reliability. These selected parameters are used for evaluating the model by analyzing the performance related to the diabetic levels with the classification and prediction report. The main objective of the proposed algorithm is to analyze and predict the diabetics of various People by considering the cholesterol attribute and blood pressure attribute with different age group of people. Figure 3 shows that the proposed model of generic diabetic prediction.

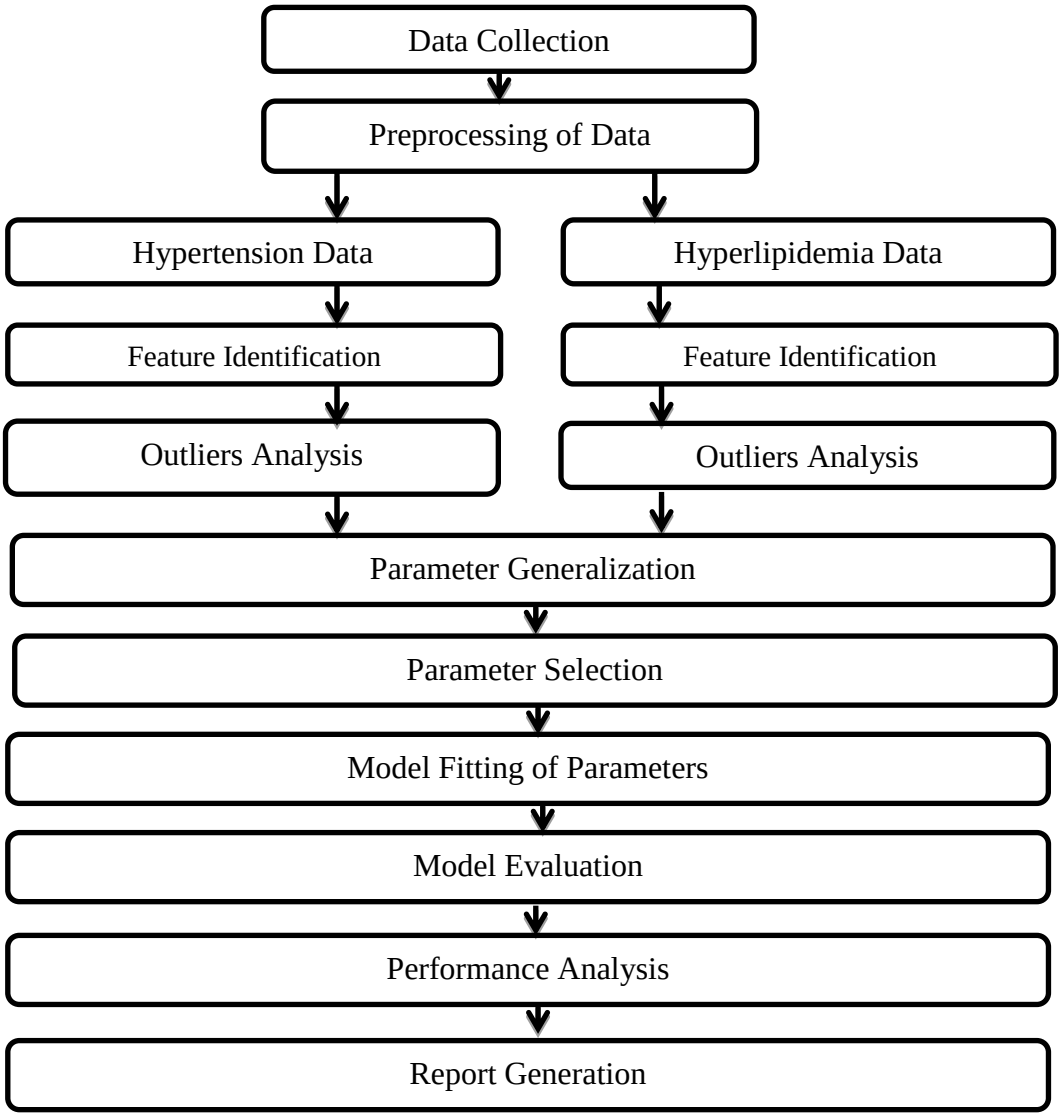

Figure 3 Proposed generic model

3. HYPERTENSION DIABETIC ANALYSIS

In medical diagnostics, monitoring the co-occurrence of the diabetics and blood pressure level is by introducing the control mechanism. It is done in two levels of operations they are inner loop based and outer loop based. Blood pressure disturbs the insulin level with different variation which is controlled by using fuzzy based model [16]. Heart beat variation is monitored by using HRV (Heart Rate Variability) measurement by considering hypertension parameter which is related to diabetics. The high risk of cardiac problems occurs due to hypertension of the

diabetic patients [17]. The blood vessels are segmented from the retinal images for doing diagnosis process especially hypertension. The segmentation process has two level of abstraction method they are MRF reconstruction based and compensation based [18]. Retinal blood vessels structural changes are detected for diagnose the hypertension related diabetic problem. Retinal images are processed with two operations such as image filtration process and reconstruction based morphological process with 90.38 % accuracy [19]. The complication related to the different properties of diabetics such as hypertension level and other blood vascular complications with various age groups with their relationship [20]. Various levels of hypertension are presented in Table 2.

Table 2 Levels of hypertension [37]

Type of Blood Pressure	**Systolic and Diastolic Levels**
Normal	<120 and >80
Hypertension [Elevated]	[120-129] and < 80
Hypertension [Stage 1]	[120-129] and [80-89]
hypertensive crisis [Stage 2]	>=140 and >=90

Hypertension with diabetes causes dangerous risks in the human, so it is identified clearly and accurately. The common causes of these combinations are obesity, infection, stress and resistance of insulin. The risk factor includes the fat in the body, uneven diet, poor sleep, age, smoking and so on. In this analysis we have used various features for diabetic analysis namely Glycosolated Hemoglobin, age,

gender, height, weight, BMI and WHR with insulin levels. According to our analysis 72 persons have diabetes because of hypertension. 248 persons and 83 persons are classified as no diabetic and getting chances respectively. The proposed algorithm uses the above mentioned parameters for prediction. Various machine learning algorithms are compared and analyzed. The proposed algorithm gives better results when compared to other models. Figure 4 gives the hypertension outliers of various models with proposed model.

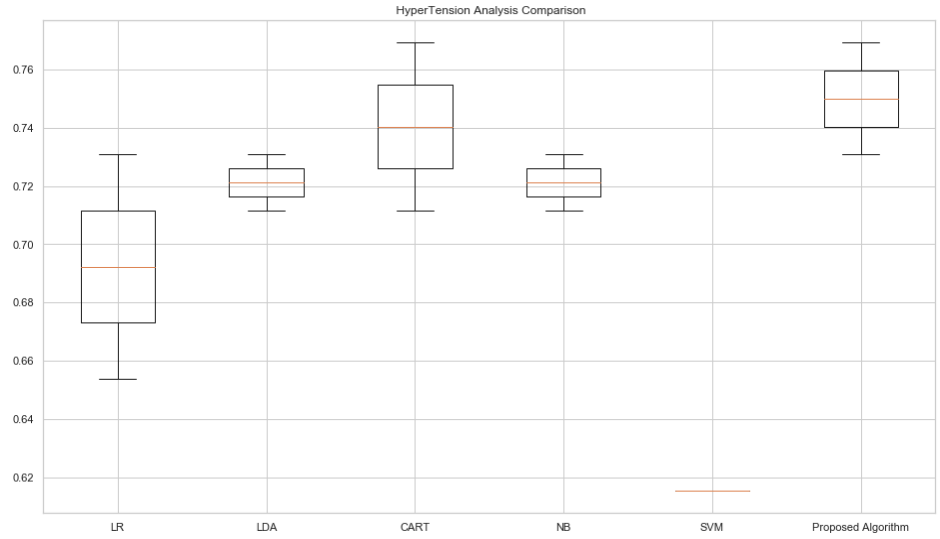

Figure 4 hypertension based diabetic analysis

4. HYPERLIPIDEMIA DIABETIC ANALYSIS

Lipid level of blood is reduced using ultrasound based models with dynamic and ad-hoc parameters. This model needs various components such as transducer, control and required power and so on. The threshold level is fixed with hyperlipidemia levels and concentration [21]. Recently hyperlipidemia has affected mostly youngsters because of an uneven food habit with liquor. The consumption of the chemical drugs leads to a negative impact on their body with heart disease [22]. There are two groups of hyperlipidemia patients namely control

and stamen group for doing respective treatments. The analysis is done in three levels such as LDL, HDL and triglyceride which are static with various kinds of abnormality [23]. The review has been completed related to the association between individual gene factors and one trait. It also extended to analyze multi gene factors with suitable detection methods. The gene category either single or multiple is summarized with various techniques and dimensions. Multi-traits perform the task such as pre-screening, selection of variables and segmentation [24]. The important factor of cardiovascular disease is hyperlipidemia, so it will be monitored carefully. A co-occurrence element of high lipid is identified based on the classification [25]. Table 2 represents the various levels of hyperlipidemia.

Table 3. Levels of hyperlipidemia [37]

Type of cholesterol	**Normal Range**	**Borderline range**	**High range**
Total cholesterol	**<200**	**Between 200 and 239**	**>=240**
LDL - bad cholesterol	**<130**	**Between 130 and 159**	**>=160**
HDL - good cholesterol	**>=50**	**Between 40 and 49**	**<40**
triglycerides	**<200**	**Between 200 and 399**	**>=400**

Hyperlipidemia with diabetes is a lipid abnormal problem in a very low level with high density manner. Type1 and type 2 diabetes mainly affect this type of problem, so it is controlled and improved by maintaining the normal level as per doctor's suggestions [26]. The proposed algorithm uses the hyper parameters for analysis namely Cholesterol ratio, gender, age, WHR and BMI. Cholesterol ratio is calculated based on the features cholesterol and HDL. The analysis provides 120 persons do not have any cholesterol abnormality and 248 persons are having high cholesterol levels. Most of the patients with diabetes are safe in cholesterol but it suffers in other factors such as obesity. Various algorithms are used to evaluate and assessed the diabetes condition, but the proposed algorithm gives maximum prediction with reliability. Figure 5 provides the hyperlipidemia outliers of various algorithms with proposed algorithm.

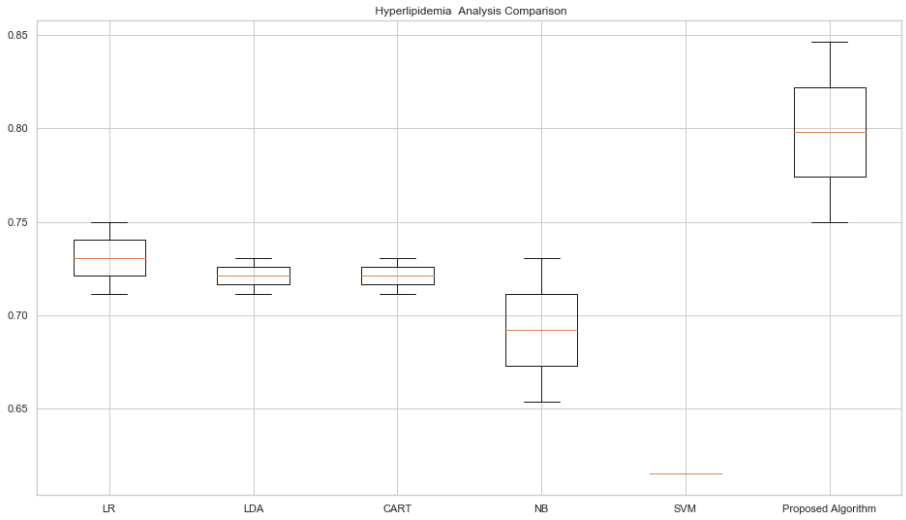

Figure 5 hyperlipidemia based diabetic analysis

5. OUTLIER DIABETIC ANALYSIS

Outliers are the objects which appear far away from the set of objects. It is measured by using distance calculation and also detected and eliminated for better accuracy. The outliers are considered as anomalies, divergence of data and so on.

The outliers are eliminated for overcoming the incorrect result over the data. GHOA is a method used for eliminating the outliers over multidimensional data with variety [27]. There are various methods used in outliers detection namely density based, distribution based and distance based which do not give good results. This is overcome by using the KNN method with two factors namely global and local factors with high efficiency [28]. The low density area in the input space is considered as an outlier than the high density area in the cluster. The graph based analysis is carried out for high quality results [29]. The outliers are classified as global, context based, collective based with the behavior is a hyper parameter. These outliers are applicable for all kinds of machine learning algorithms such as supervised to semi supervised [30]. Outlier analysis finds the relevant patterns or samples from unusual input samples for achieving good accuracy. Outliers are considered and rejected based on the relevancy and contribution towards the final result [31]. Figure 6 and figure 7 illustrates the blood pressure and cholesterol based outlier analysis respectively.

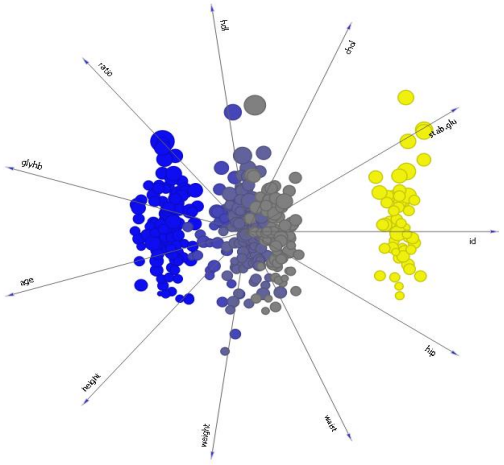

Figure 6 hypertension outlier analysis

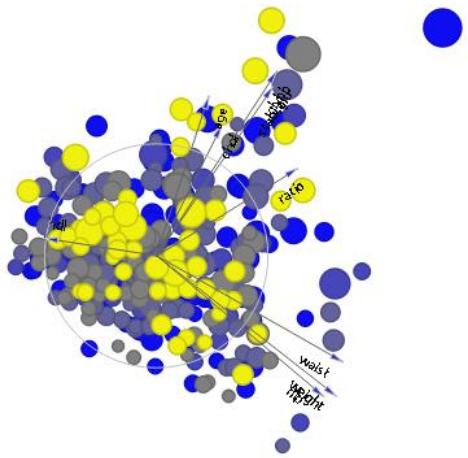

Figure 7. hyperlipidemia outlier analysis

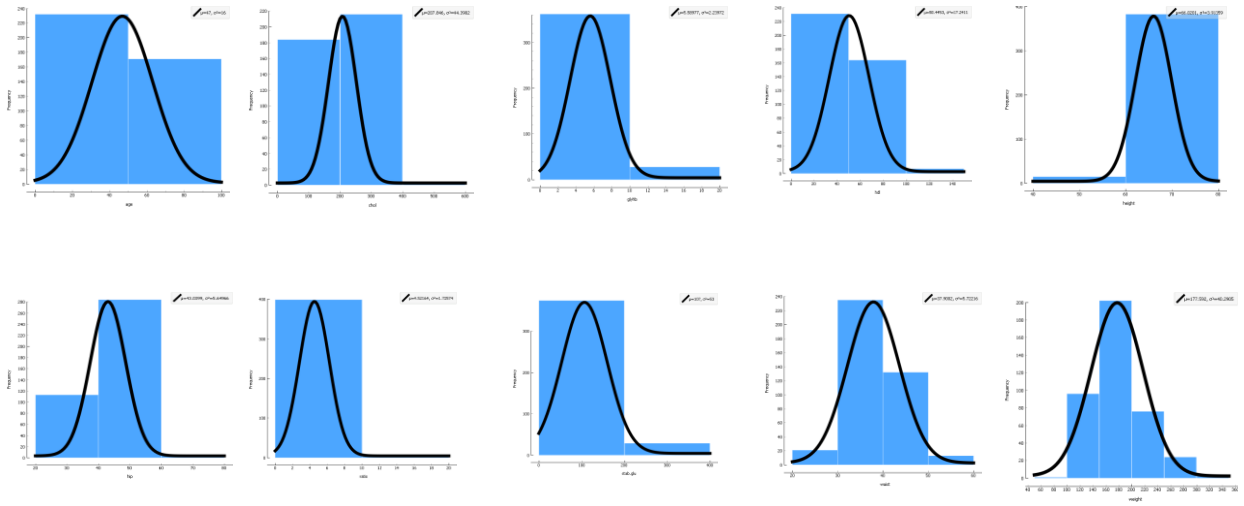

Figure 8. Outlier identification of features

Outliers are the deviation or variance of the data samples with overall pattern. Multidimensional outliers are identified based on N features space (i.e. N is the number of features). Outliers are the deviation or variance of the data samples with overall pattern. Z-score value is calculated for all features involved in the proposed algorithm. Z-score normally measures the relationship of a group of features. If the z-score is 'o' then there is no deviation in the data otherwise variation in the data set leads the production of outliers. In our analysis all z-score related to features are negative which means that it is below the threshold value in normal distribution. This value gives the minimum value almost close to zero, so it never affects the accuracy in the model. Threshold level features identification is shown in figure 8 and z-score is calculated using equation (1). Diabetic analysis based on z-score is presented in Table 4.

$$\text{Z - score} = \frac{\text{x} - \mu}{\sigma} \qquad \textbf{(1)}$$

Table 4. Z-score for diabetic analysis

Features	***μ***	***σ^2***	***x***	***z-score***
Age	47	16	46.85112	-0.03722
Chol	207.846	44.3902	207.33	-0.07745
Glyhb	5.58977	2.23972	5.409454	-0.12049
HDL	50.4453	17.2411	50.3201	-0.03015
Height	66.0201	3.91359	65.20099	-0.41405
Weight	177.592	40.2905	177.1514	-0.06941
Hip	43.0399	5.64966	42.8263	-0.08986
Ratio	4.52164	1.72574	4.51042	-0.00854
Stab	107	53	106.6725	-0.04499
waist	37.9002	5.72216	37.71216	-0.07861

6. RESULT AND DISCUSSION

The diabetic disease operation speed is enhanced by using classification with automatic inspection capability. Multiple features are used for classification problems faced by the traditional models. This problem is overcome by using KNN with multiple labels for classification. It gives more accuracy than binary classification models for detecting and classifying the diabetics [32]. It is not suitable for large scale data set, so it will be analyzed based on the gender based diabetics detection. A diabetic causes the vision problem of humans because it is an eye disease for diabetic patients. The early detection of this problem is done by implementing an automated diabetic diagnosis model. Support vector Machine model is used for segmentation of optic regions of image. It achieves 91% of sensitivity and 90% of accuracy [33]. This model only uses the retinopathy diabetic images for analysis, so it suffers the accuracy problem. It is improved by using texture analysis of images with multiple attributes. Traditional method of handling diabetic classification with binary which produces only two results either

1 or 0 (i.e. 1-yes and 0-no). DRAP is a tree based approach that uses multidimensional features for analysis with the accuracy score of 76.5 % [34]. Diabetic patients suffer a problem of exudates which are done using an automated model. The early detection of this problem is carried out using neural networks with deep layers using morphological based algorithms with 91% accuracy [35]. The diabetic detection at the earlier stage is a tedious task because of various irrelevant data present in the data set. The preprocessing is a complex task based on the data sets used in the analysis. The hyper parameters are selected and enhance the performance using an Adaboost model with 92 % accuracy [36]. The precision, recall, F-measure and accuracy is exposed in equation (2), equation (3), equation (4) and equation (5) respectively.

$$precision = \frac{True\ Positive}{(True\ Positive + False\ \ Positive)} \quad \textbf{(2)}$$

$$recall = \frac{True\ Positive}{(True\ Positive + False\ \ Negative)} \quad \textbf{(3)}$$

$$F - Score = \frac{(2 * precision * recall)}{(precision + recall} \quad \textbf{(4)}$$

$$Accuracy = \frac{True\,Positive + True\ Negative}{Total} \quad \textbf{(5)}$$

Table 5. Hypertension Diabetic Analysis

Classification Model	Performance Measurement				
	Precision %	**Recall %**	**F-Score %**	**Accuracy %**	**AUC %**
KNN	75.4717	79.06977	83.33333	87.17949	88.88889
SVM	75.67568	80.95238	83.72093	87.23404	89.74359
Random Forest	77.55102	81.08108	84.48276	87.5	90
Neural Network	78.37838	82.6087	84.61538	88.09524	90.2439
AdaBoost	78.57143	82.97872	85	88.37209	90.56604
Proposed Algorithm	79.7234	83.01887	86.04651	88.70968	91.48936

Table 6. Hyperlipidemia Diabetic Analysis

Classification Model	Performance Measurement				
	Precision %	**Recall %**	**F-Score %**	**Accuracy %**	**AUC %**
KNN	87.5	90	92.5	97.82609	79.06977
SVM	88.09524	90.2439	93.75	104.4444	80.95238
Random	88.37209	90.56604	93.87755	113.9535	85
Neural	88.70968	91.48936	95.12195	75.4717	86.04651
AdaBoost	88.88889	91.66667	95.2381	75.67568	90.56604
Proposed	89.74359	92.30769	97.4359	77.55102	91.48936

Table 7. Error Analysis

	Hyperlipidemia Diabetic Based				**Hypertension Diabetic Based**			
Model	**MSE**	**RMSE**	**MAE**	**R2**	**MSE**	**RMSE**	**MAE**	**R2**
KNN	11799.5	108.6255	63.09459	0.942255	391.2678	19.78049	15.35188	0.707103
SVM	186771	432.1701	322.7261	0.085965	843.6542	29.04573	22.23362	0.368453
Random Forest	11026.54	105.0073	67.01156	0.936037	443.0823	21.04952	15.81275	0.668315
Neural Network	752899.9	867.6981	747.0601	-2.6846	2083.79	45.64855	37.06704	-0.55989
AdaBoost	12692.58	112.6613	77.89471	0.947884	532.7429	23.08122	17.20297	0.721197
Proposed Algorithm	10692.58	102.6613	88.89471	0.917884	10692.58	102.6613	88.89471	0.917884

Performance measurement of the hybrid algorithm is illustrates in Table 5 and Table 6 respectively. Table 7 represents the error analysis of the proposed algorithm with machine learning model. The proposed algorithm uses the machine learning approach by considering the parameters like hypertension, hyperlipidemia with the relationship of the insulin level and sugar level. The existing model uses only specific combination with limited features which leads the accuracy and performance problem. These issues are identified and solved by using broader features with corresponding attributes in generic manner. The accuracy of the proposed system is 88.37% and better when compared to other algorithms with high robust and efficiency.

7. CONCLUSION AND FUTURE WORK

Diabetes is a disease which affects the human body because of high sugar levels present, so it will be controlled properly with proper treatment. There are various types of diabetes namely type I and type II. The proposed algorithm considered various features with high end attributes in an optimal manner. Various features have been selected and establish the relationship for diabetic identification. Existing models of detection use only specific categories, but the proposed algorithm uses the hybrid with multi features relationship for achieving high performance. Different blood pressure and cholesterol is considered by assessing the correct level of sugar and insulin. Outlier detection gives more accuracy using normal distribution with threshold. The main objective of the proposed algorithm is a hybrid version of diabetic detection with multi-dimensional input space. It also produces high accuracy. In the future this model can be applied to different disease on medical domain for getting precise result.

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