Nanotechnology Perceptions
ISSN 1660-6795
www.nano-ntp.com

A Literature Review On Decision Support System Models To Predict Diabetic Retinopathy Using Historical Data, And Machine Learning Techniques

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The expansion of health sciences and IT has been made possible by electronic health records, which in turn have led to the creation of enormous data sets. Knowledge Discovery from Data (KDD) or data mining refers to the technique of automatically finding patterns that stand in for knowledge. Massive databases, data warehouses, or information repositories hold all the known information. Damage to the retina's blood vessels is known as diabetic retinopathy. The retina is the rear of the eye's light-sensitive layer of cells. The results of this are a reduction in blood flow and blurred eyesight. In addition, swelling and hemorrhage are seen. New blood vessels may start to sprout at some stage, but further problems may develop. Most cases of diabetic retinopathy affect both eyes. Diabetes mellitus type 2, gestational diabetes, and insulin-dependent diabetes can all lead to diabetic retinopathy. Those who have lived with diabetes for an extended period are more likely to develop retinopathy. It is critical to develop a Clinical Decision Support System to assist physicians in establishing the diagnosis of this condition because of how challenging it is. Knowledge extraction from medical databases is crucial for accurate medical condition diagnosis. This research aims to conduct a comprehensive literature evaluation of machine learning approaches used by decision support systems and clinical decision support systems for data balance and diabetic retinopathy prediction.

Keywords— DSS Concepts; Clinical Decision Support Systems; Diagnosis; Diabetes; Diabetic Retinopathy; Data Mining.

I. INTRODUCTION

Academic researchers have studied computerized Decision infrastructure for about fifty to five decades. Using analytical models and computers to aid in crucial decision-making and company planning is the basic idea behind a Decision Support System. All operations, decision-making, and managerial tasks should be facilitated by these decision-support systems. The voting feature's error rate was decreased. Many industries use decision support systems; some examples are healthcare, banking, and law enforcement. According to Asemi et al. (2011), a management information system model's decision support system model regularly generates a report based on the data input into the environment. Clinicians rely heavily on clinical decision support systems when making patient-related decisions. Reducing the occurrence of medical mistakes is the main goal of clinical decision support systems (Hannah & Ball, n.d.).Computerized software with a clinical knowledge base database is compared to patient information in a clinical decision support system (Sutton et al., 2020). Predicting diseases like lung cancer is a common use case for clinical decision support systems in many areas of healthcare (Han et al., 2020). Chronic disease of the kidneys can be detected and predicted with the use of CDSS (Hamedan et al., 2020). It predicts the unusual risk and severity of COVID-19 patients and is used in clinical decision-making as well (Murri et al., 2022). Wu et al. (2020) reported that the study had a 97.5% success rate. According to Yan et al. (2022), decision support systems aim to predict when coronary artery stenosis will begin in individuals who are suspected of having coronary heart disease. One of the many approaches that may be used to predict the probability of acquiring diabetes is the utilization of Deep Learning algorithms. According to El Mohajir et al. (n.d), one of the ways is the Clinical Decision Support System.

Three groups have distinguished between knowledge-based and non-knowledge-based clinical decision support systems: Ng et al., Li et al., and Zhou et al. Several machine learning and statistical pattern recognition techniques rely on these systems.

II. DATA MINING

Data Mining is a method of exploring and gathering unfamiliar patterns from enormous amounts of data. It helps the decision-makers to understand and empower the different forces that control decision-making in their respective fields. Data Mining is a very advantageous field in Medical and Healthcare data analysis. It is used extensively for diagnostic accuracy, helping reduce the overall expenditure for treatment and saving human resources. Data Mining has been helpful in many fields, such as Life Insurance, acquiring and retaining new customers, policy designing, and policy selection (Devale, 2012). It can be deployed in different fields of the education sector to predict student performance, etc. (Mengash, 2020). It can also be integrated with GIS for pavement management and road maintenance (Zhou et al., 2010). Various data mining techniques are used for making stock investment decision-making (Cheng et al., 2021). Data mining capabilities could lead to increased performance in Human Resource Management and strategic decision-making (Goyal & Ahson, 2008).

Data mining plays a significant role in clinical decision support systems nowadays. Using data mining techniques, the researchers developed a model to predict the onset of illnesses such as diabetes (IEEE Staff, 2017).According to Baitharu and Pani (2016), a CDSS model was suggested for the purpose of predicting liver illnesses using data mining techniques. Heart attack prediction using logical regression was proposed by Tsao et al. (2018) and BKavihta et al. (2010), whereas neural networks proposed a CDSS utilizing data mining approaches. According to Chen et al. (2017), I investigated, evaluated, and assessed the state of the art in data mining from EHRs. Their research led them to believe that data mining is an exciting new field with the potential to improve healthcare awareness screenings and decision-making.

According to Niranjan et al. (no date given), They suggested a way to find brain cancers using mining algorithms."Dehghanzadeh et al., 2021" Their data mining practice comparison aimed to predict COVID-19 patients' in-hospital mortality.

The use of data mining techniques in the study of diabetes and diabetic retinopathy is currently attracting a lot of attention from researchers for many reasons. A plethora of data is at your fingertips. Third, the disease's severity and the degree of vision loss are directly correlated with the rising cost of care (Orji et al., 2021). Fourth, there are many clinical and pathophysiological implications of retinopathy, the most common diabetic complication. Medical and healthcare providers should make preventing it their top priority in this situation, and data mining is the best way to do it.

III. **LITERATURE REVIEW**

Diabetic Retinopathy may show no symptoms or minor vision issues at the beginning but may ultimately lead to vision loss. Anyone having type 1 or type2 diabetes can develop this condition, and the longer the illness, the more prone one is to Diabetic Retinopathy.

A. Symptoms and Clinical Features of Diabetic Retinopathy

There might be no symptoms in the early stages of diabetic Retinopathy. As the illness grows, the patient might develop blurry vision, fickle vision, gloomy or void areas in vision, and vision damage spots or dark strings floating in the vision, also known as floaters in medical terms. Diabetic Retinopathy is best detected with a complete dilated eye test (www.mayoclinic.org).

Several clinical abnormalities can be present in the retina, like Microaneurysms (MA), the most preliminary sign of retinal damage, consisting of a red spot with a size of less than 125µm and sharp margins. The next type is Hardexudates—where the proteins and lipoproteins leak through the abnormal retinal blood vessels (Mookiah et al., 2013).

B. Literature review of various models

Much of the research has made use of the Pima Indian data set. The majority of researchers have used some data mining techniques in their quest to create a model that can improve the accuracy of DR forecasts and predictions. According to Acharya et al. (2012), Balakrishnan et al. (2012) suggested a computerized approach to regular, NPDR, PDR, and ME class classification using texture parameters and SVM, and the method achieved an average accuracy of 85.2%. Sangi et al. (n.d.) used Tiberius and SPSS to build multiple models for predicting retinopathy. The Durbin-Watson test was also utilized by Anathapadmanaban and Parthiban (n.d.-a.), who likewise obtained findings between 1.5 and 2.5. The SVM classifier had the highest accuracy rate of 79.5%. In 2014, Latha introduced a system that used Neuro-Fuzzy based on feature extraction to diagnose retinopathy with an accuracy rate of 96.2%. The study's public health statistics were derived from the American National Health and Nutrition Examination Survey (NHANES) cross-sectional data collection, which only covers persons with diabetes (Ogunyemi and Kermah, n.d.-a). A Lasso tool was used to choose subsets of features. We implemented many ensembles, such as RUSBoost and AdaBoost.M1. The clinical dataset demonstrated a moderate degree of predictive ability, according to the results. In terms of accuracy, sensitivity, specificity, and area under the curve (AUC), the top RUSBoost ensemble achieved 73.5%, which is considered satisfactory.

According to Getharamani and Balasubramanian (2016a), Their recommended procedure included pre-processing images, then learning with both supervised and unsupervised methods, and finally post-processing the images. To arrange pixels, the model used K-means clustering. A rate of 95.36% accuracy has been reached using this methodology.Research by Chandrasekaran and Nagarajan (2015a) employed the basic K-means algorithm to create the model. The data underwent preprocessing, three-stage clustering, and subsequent classification. Alli and Somasundaram (2017) introduced SimpleCart. We presented a model that uses ML-BEC to find retinal features that can detect DR early on. The methodology was broken down into two parts. The initial step involved extracting the candidate objects from the Retinal Images. Using a machine learning technique called t-distributed Stochastic Neighbor Embedding (t-SNE), the candidate objects were selected based on specific features and extracted. Using (Power, n.d.) to activate the classifiers was the subsequent step. Decision support systems are utilized by several industries, including healthcare, finance, and law enforcement, to name a few. Asemi et al. (2011) state that a report is frequently generated by the decision support system model of a Management Information System Model using the data supplied into the environment. Clinical decision support systems are vital to clinicians when it comes to making important judgments about patients. The primary objective of clinical decision support systems is to decrease the frequency of medical errors (Hannah & Ball, n.d.).Clinical decision support systems compare patient records with software that has a database of clinical knowledge (Sutton et al., 2020). One such use of clinical decision support systems in healthcare is the prediction of illnesses such as lung cancer (Han et al., 2020). The application of CDSS allows for the detection and prediction of chronic renal disease (Hamedan et al., 2020). This is a t-SNE.Second, we processed the one-dimensional dataset using the CNN approach with a merged BN layer. The classifiers were also applied at this point. The experiment yielded results with a 95% confidence level. In their 2019 research, Sun and Zhang analyzed EHR data from 301 hospitals using five different machine learning models: Logistic Regression (LR), Support Vector Machines (SVM), Random Forests (RF), Decision Trees (DT), and Naïve Bayes (NB). According to the results, Random Forest achieved an accuracy level of 92%. After using Random Forest, the machine learning model achieved an accuracy rate of 92% (Sun & Zhang, 2019).

They tested many data mining classification algorithms for DR diagnosis in their study (Vadloori et al., n.d.-a). With an accuracy of 80.15 percent, the Naïve Bayes classifier was determined to be the most effective. (Hamed et al., 2020) Using a combination of Logistic Regression, Decision Tree, and Artificial Neural Network, they put out a data mining model. An accuracy rate of 63.36% was recorded by the Forward selection method model in the Logistic Regression, according to the results (Sunil Salvi et al., n.d.). Reference: Gadekallu et al., 2020.

A way to identify DR early was proposed by Behera (2020) using machine learning and image processing. The retinal fundus image's characteristics would be inputted into the Support Vector Machine (SVM) for the prediction. The Radial Basis Function (RBF) kernel outperformed the others when fed the identical set of features, with an accuracy of 97.2%.It was asserted (Alfian et al., 2020). To find and extract data from specific risk variables, we employed Deep Learning techniques. Predicting diabetic retinopathy (DR) in its early stages is now feasible with the use of a Deep Neural Network (DNN) and recursive feature elimination (RFE). The resulting accuracy percentage was 82.033 percent.

(W. Li et al., 2021) Using a large dataset consisting of 32452 inpatients, researchers examined DR risk variables and developed ML prediction models. They built a prediction model using XGBoost, random forests, logistic regression, and support vector machines. The findings were illustrated using Shapley's additive explanation. The accuracy rate of 89% was achieved by the Naïve Bayes-based model proposed by Evirgen and Çerkezi (n.d.).(The 2019 research by Fiarni and coworkers) A model that achieved an accuracy rate of 68% was proposed by merging Naïve Bayes, C4.5 Decision Tree, and K-means Clustering, respectively. Machine learning and deep learning methods have been created by several researchers; for instance, (Shen et al., 2021a), (J. Li et al., 2022), (Pragathi & Nagaraja Rao, 2022), and (Sumathy et al., 2022). While KNN achieved 88.9% accuracy, the Boosted tree attained 90.1%. Several data mining approaches were used to generate models of diabetic retinopathy, as shown in Table 1.

TABLE I LITERATURE REVIEW OF VARIOUS MODELS

Author	**Method Method**	**Sampling Technique**	**Accuracy**
(Acharya et al., 2012b)	Image Processing SVM Classifier	Not Available	85.2%
(Balakrishnan et al., 2012b)	Association rules from Apriori algorithm and CBR	Not available	Not available
(Predictions-Using-Data-Mining-and-Case-Based-	Data mining and CBR	Not available	73%

Reasoning-a-Case-Study-for-Retinopathy, n.d.-b)			
(Sangi et al., n.d.)	ANN and regression analysis	Not available	Not available
(Ananthapadmanaban & Parthiban, n.d.-b)	Naive Bayes and Support Vector Machine	Not available	83.37%
(Latha, 2014)	Neuro-Fuzzy	Not available	96.2%
(O. Ogunyemi & Kermah, n.d.-b)	RUSBoost and AdaBoost.M1	Not available	73.5%,
(Geetharamani & Balasubramanian, 2016b)	K-means	Not available	95.36%
(Nagarajan & Chandrasekaran, 2015b)	Simple K-means, andom Tree, NaiveBayes, Simple Cart and Simple Logistics Simple Cart	Not available	Simple Cart: Accuracy Value:1

(Amin et al., 2017)	KNN, SVM, Image Processing	Not available	98.58%.
(Piri et al., 2017)	Logistic regression ANN, Decision tree, Random Forest	SMOTE	92.76%
(Somasundaram & Alli, 2017)	AMAD ,ADM-DR, SIRSE, and MSNNSC. ML-BEC	Not available	ML-BEC method achieves 22%accuracy compared to AMAD, whereas it resulted in 32% accuracy when matched to AMD
(Anant et al., 2017)	Image processing and KNN classifier	Not available	97.75%
(Tsao et al., 2018b)	Support vector machines, Decision trees, Artificial neural networks, and Logistic	Not available	79.5%

	regressions		
(Sun, 2019)	CNN	Not available	95%
(Sun & Zhang, 2019)	Random Forest	Not available	92%
(Vadloori et al., n.d.-b)	A k-nearest neighbor, random forest classifier, support vector machine, regression tree classifier, logistic regression, and the Naïve Bayes theorem	Not available	80.15%.
(Khairudin et al., 2020)	Logistic Regression, Decision Tree, and Artificial Neural Network	Not available	66.36%

(Sunil Salvi et al., n.d.)	CNN, Transfer Learning	Not available	95%
(Gadekallu et al., 2020)	DNN	Not available	97%
(Behera, 2020)	SVM, CLAHE	Not available	97.2%
(Alfian et al., 2020)	DNN, RFE	SMOTE	82.033%
(W. Li et al., 2021)	XGBoost algorithm, logistic regression, random forest, and support vector Machine	Unknown	
(Evirgen & Çerkezi, n.d.)	Naive Bayes	Unknown	89%
(Fiarni et al., 2019)	Naive Bayes, C4.5 Decision Tree, K-means Clustering	Unknown	68%
(Shen et al., 2021b)	XGBoost and stacking	Unknown	83.95%
(Pragathi & Nagaraja Rao, 2022)	Naïve Bayes,	Unknown	85.61

(Sumathy et al., 2022)	RF, SVM Logistic regression, K closest neighbour, support vector machine, bagged trees and boosted trees	Unknown	86.1%

C. **Review Analysis**

Analyzing the above review, it can be interpreted that many researchers have used a diabetic dataset without revealing its source. Many have used Dataset from unknown sources. Some researchers have taken different datasets from EHRs of different hospitals or personal interviews and questionnaires. Some researchers have used the same classifiers but obtained different accuracy rates. For example (Acharya et al., 2012c) and (Pragathi & Nagaraja Rao, 2022)used SVM classification but achieved an accuracy of 85.2% and 76.96, respectively.

D. **Historical Data**

E. Historical Data is the data that is collected and related to past events and conditions or circumstances concerning a particular field or enterprise. It may be generated automatically or gathered manually. It attempts to find out the critical meaning or a subtle difference, the events, and the people that could have influenced the past and shaped the present. Historical data has been vital in data mining and predicting many different events. For example, in their research (Borzooei et al., 2019)Predictions and long-term preparedness for extreme climatic conditions can be made possible based on the model developed using historical data. According to (Ao & International Association of Engineers., 2010) the Financial Stock Market forecast is possible by data mining historical data.

1) **Data**: In general terminology, data can be any raw facts, a set of characters, a set of numbers, a set of pictures, etc. In computer science, terminology data is a collection of the number stored as bits on the computer's main memory; these bits can contain information about text, images, sound, or video. The essential element for data mining technologies is data, which forms its core. With data, mining techniques are helpful.

2) **Sampling Techniques in Data Mining**: Sampling is a statistical technique that uses a portion of a bigger dataset to find trends and patterns. In order to draw conclusions about a large population, this subset of a larger dataset is used. Among the many sampling methods used in data mining are the Synthetic Minority Oversampling Technique (SMOTE), Random Undersampling, and Random Oversampling. Knowledge is essential for diagnostic purposes in the clinical diagnosis of any illness. Typically, if the data were more uniformly distributed and collected from multiple sources, one category would have more instances than the other. During the classification process, these data imbalances pose a significant challenge. Many DSS have already started using SMOTE. In their 2018 study, AlAgha et al. suggested a model that can distinguish between people who do not have β-thalassemia and those who do by utilizing classification models like k-Nearest Neighbor, Decision tree, Naïve Bayesian, and the multilayer perceptron neural network. To fix the problems caused by the extremely unbalanced class, they used SMOTE to level the dataset. In order to find significant flaws in internal control, Nasir et al. (2021) also created a DSS. Taking into account the SMOTE sampling technique helped rectify the learning problem caused by the unbalanced data.

3) **Prediction of Diabetic Retinopathy By removing class imbalance**: Scientists have created a number of models and algorithms to use SMOTE for diabetic retinopathy prediction.A deep learning model for DR detection was trained using a two-stage method, utilizing the Decision Tree and NASNet-Large deep CNN. As stated in the study by P. et al. (2021). They began by categorizing the data. They used the Synthetic Minority Oversampling Technique in the Deep Learning Module during the second stage to resolve the issue of imbalanced training data. Two groups were created from the data: one for internal validation and training purposes and another for external testing. (The study conducted by O. et al. and colleagues in 2021) These include ANN, Random Forest, Support Vector Machines, A combination of XGBoost, Deep Learning, and Gradient Boosting for a quartet of classifiers. Using the two-class sampling method, the researchers came up with 10 distinct modeling sampling combinations, such as SMOTE and majority class undersampling. With an AUC of 0.81, the top classifier was determined by the Deep Neural Network Model.According to Homayouni and colleagues (2022), Following the development of an algorithm to identify high-risk DR patients by lowering the number of predictors and utilizing a smaller set of variables, the Progressive Ablation Feature Selection approach using XGBoost was introduced. Using the selected characteristics, the system could predict which patients would have DR. After the dataset was acquired from several US hospitals, it was balanced using SMOTE. The area under the curve (AUC) performance with standard deviation for the model was 98.02 with 14 features, 97.66 with 12 features, 96.61 with nine features, and 95.73 with six features. During 2018, Cao et al. It was proposed that graph kernels be used as a basis for multi-instance learning. Oversampling and instance-level undersampling were recommended to improve performance. A precision of 0.916 was produced by the procedure. Microaneurysms are the first signs of diabetic retinopathy. Source: Wang et al., 2017. In addition to borderline SMOTE and data cleaning methods, I have proposed using an AVM classifier. Additionally, they proposed BSMOTE-Tomek and BSMOTE-ENN, two hybrid algorithms that, with the help of modified SVM, could accurately distinguish between real and false microaneurysms. According to Ogunyemi et al. (n.d.), Using a dataset that shows class imbalance, we compared and studied different machine-learning techniques for predicting

retinopathy. An area under the curve (AUC) of 0.754 proved that the ANN using SMOTE performed the best.

TABLE II LITERATURE REVIEW OF DR PREDICTION MODELS USING SMOTE

Author	**Method Method**	**Sampling Technique**	**Accuracy**
(P. N. Chen et al., 2021)	Decision Tree, Deep Learning and CNN	SMOTE	For Train & Validation Set:89.79 For Test Set 87.50
(O. I. Ogunyemi et al., 2021)	RF, SVM, XGBoost, ANN, DNN, Gradient Boost	SMOTE	AUC 0.81
(Homayouni et al., 2022)	RFE, LASSO & XGBoost	SMOTE	98.02(14 features), 97.66(12 features), 96.61(9 features), 95.73(6 features)
(Cao et al., 2018)	mi-Graph algorithm	SMOTE	0.957
(Wang et al., 2017)	ENN, SVM	SMOTE	Not Available
(O. I. Ogunyemi et al., n.d.)	Logistic regression, SVM, ANN	SMOTE	AUC 0.754

IV. CONCLUSION

The primary purpose of this research was to conduct a comprehensive literature review on the various machine learning methods used in clinical decision support systems and decision support systems in general for the purpose of predicting diabetic retinopathy and balancing data. In order to accomplish these goals, four primary research questions have been formulated during this review. To begin, we need to know which machine learning methods are considered industry standards for use in CDSS. Machine learning techniques are currently the subject of a great deal of research aimed at illness prediction. An important area for research is to identify the most popular and reliable methods used for this purpose. The second most important thing is to figure out how to use these methods to foretell cases of diabetic retinopathy. A more accurate machine-learning model for Diabetic Retinopathy prediction could be possible with this knowledge since it allows for the exploration and analysis of potential new areas of improvement. The third inquiry concerns the identification of essential characteristics for the development of the CDSS model for Diabetic Retinopathy risk prediction. A major component is doing research to identify the primary factor that causes the disease. Research into the causes of diabetic retinopathy, specifically the key factors that have so far eluded identification, is crucial. Lastly, the fourth inquiry concerns the best way to verify the accuracy of the Diabetic Retinopathy risk prediction model used by Clinical Decision Support Systems. In order to demonstrate that a model for predicting the risk of diabetic retinopathy is valid, what are the most important and crucial factors or parameters to consider? The identification and screening of Diabetic Retinopathy prior to its progression would result in disease prevention, as stated by Bora et al. (2021). The accuracy and cost-effectiveness of disease prediction could be enhanced through future research that makes use of cutting-edge technology and machine learning techniques.

CONFLICT OF INTEREST

There is no Conflict Of Interest.

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