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Evaluation and Improving Prediction Accuracy on Healthcare using Classifier algorithms

Himani Mahur[1], Swati Jadon[2], Ankush Sharma[3]

[1]M.tech., Research Scholar, Department of Computer Science& Engineering, Gurukul Institute of Engineering & Technology, Kota, Rajasthan

[2]Assistant Professor, Department of Computer Science& Engineering, Gurukul Institute of Engineering & Technology, Kota, Rajasthan

[3]Assistant Professor, Department of Computer Science& Engineering, Modi Institute of Technology, Kota, Rajasthan

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ABSTRACT: Accurate projections enhance patient outcomes. Classifiers may improve prediction accuracy. Healthcare professionals must gather and analyse data to evaluate classifier prediction accuracy. Clinical data includes medical histories, test results, etc. Preprocessing and cleaning data guarantees accuracy and analytical ready. Logistic regression, decision trees, and random forests help healthcare staff analyse and predict data. Accuracy, precision, recall, and F1 score measure classifier performance. Feature selection, data augmentation, and ensemble methods may improve healthcare prediction. Adding data enhances classifier performance, whereas feature selection chooses the most relevant data properties. Ensemble classifiers improve performance. Classifiers help doctors increase prediction accuracy and provide high- quality care. Classifying data using these algorithms improves medical decisions and patient outcomes.

AI and ML have improved medical research. Algorithms may give patient diagnostic information that simplifies and verifies decision-making. A binary classification model employing SVM, Logistic Random Forest, or KNN may automate this procedure.In this study, we train a neural network to predict a class's probability rather than its class. We then design a new classifier using these probabilities using class thresholds. The new method's shifting probability threshold yields superior outcomes.

Keywords : Logistic Regression, Prediction accuracy, Healthcare, Classifier, Machine learning, Performance metrics, Medical data, Decision trees, Random forests,

I. INTRODUCTION

In recent years, the healthcare industry has witnessed a significant transformation in the way medical data is collected and analyzed. The availability of vast amounts of data has opened up new opportunities for healthcare professionals to make more informed decisions and improve patient outcomes. One way to leverage this data is by using classifiers, which are machine learning algorithms that can analyze and categorize data. Evaluating and improving prediction accuracy through classifiers has become an essential tool for healthcare professionals to provide high-quality care to their patients. By using various techniques such as feature selection, data augmentation, and ensemble methods, healthcare professionals can improve prediction accuracy and make more informed decisions. In this context, this article explores the key concepts and techniques involved in evaluating and improving prediction accuracy on healthcare through classifiers.

Medical requirement is now a days is essential for all human being, government planning to supply a lot of facilities relating to this sickness, which is still hospitalised and is a recentcomer to the international scene. The main risk factors vary by country, but cholesterol, blood pressure, smoking, exercise, and food are notably affected. Although while hereditary factors still play a part, today's major risk variables are determined by lifestyle. Life may be greatly extended with an early and precise diagnosis, followed by the right course of therapy.

The process of medical diagnosis must be automated as a result of its complexity in order to assist medical professionals in their diagnostic work. Data mining is growing in popularity in the healthcare sector as a reliable diagnostic method is needed to uncover untapped and crucial information in medical data. Data mining may be used to examine patient information in order to identify causes and symptoms and provide suitable digital storage solutions. Also, it may find best practises in clinical care to aid in the development of norms and standards of care. Several academics have recently shown a greater interest in creating diagnostic software or healthcare apps that improve treatment outcomes by identifying illness patterns and symptoms and prescribing more effective therapies. For instance, studies that identify illnesses' causes and recommend effective treatments. By physically seeing patients or using lab test facilities, a diagnosis is made by identifying the sickness or ailment. The patient's medical history forms the basis of the diagnosis. Every time a patient is admitted to the hospital, doctors must conduct a lengthy diagnostic procedure that will have an impact on the patient's health. In order to shorten diagnosis times and improve diagnostic accuracy, it has become increasingly difficult to develop trustworthy and efficient medical decision support systems.

II LITERATURE REVIEW

In recent years, healthcare professionals have shown an increasing interest in leveraging machine learning algorithms to improve prediction accuracy in healthcare. Classifiers, in particular, have proven to be effective in analyzing and categorizing medical data to make more informed decisions and improve patient outcomes.

One study by **Katsos, K. and Johnson et.al. (2023)** explored the use of a classifier to predict hospital readmissions. The study used logistic regression and decision tree algorithms to analyze patients at a high risk of readmission are identified using electronic medical records. The classifier's accuracy in predicting readmissions was 77.8%, with an F1 score of 0.76, according to the study's findings.

Another study by **Shaoxiong Ji and Pekka Marttinen et.al(2023)**used a random forest classifier to predict sepsis in patients using electronic health records. According to the research, the classifier had a sensitivity of 95.5% and a specificity of 98.7% for correctly predicting sepsis. The results demonstrated that the classifier performed better than other methods like decision trees and support vector machines.

To improve prediction accuracy, healthcare professionals have also used various techniques such as feature selection, data augmentation, and ensemble methods. For example, a study by **Yong Li and Li Feng(2022)** used a feature selection technique to identify the most relevant features in predicting sepsis. The study found that the selected features improved prediction accuracy by 7.8%.

Another study by **Dimitrios Zikos and Nailya DeLellis (2022)**used a data augmentation technique to generate additional data for predicting diabetic retinopathy. The study found that the augmented data improved prediction accuracy by 4.6%.Ensemble methods have also been used to improve prediction accuracy in healthcare. For example, a study by **Jules Le LayID and Edgar Alfonso-Lizarazo et.al.(2022)**used an ensemble of deep learning models to predict heart disease. The study found that the ensemble model outperformed individual models and achieved an accuracy of 91.5%.

Suresh K Bhavnani and Weibin Zhang et.al (2022) The objective of this research was to create and assess an innovative analytical framework, known as the Modelling and Interpreting Patient Subgroups (MIPS), utilizing a three-phase modelling process consisting of classification, prediction, and visual analytical modelling. The classification modelling was employed to precisely classify patients into subgroups and estimate their expected outcome, while the prediction modelling was used to forecast a patient's outcome.

Perera T, Grewal E, Ghali WA, et al.(2022) The focus of this investigation was to assess the connection between the quality of discharge care as perceived by patients and their post- discharge outcomes. Furthermore, the aim was to identify the factors that contribute to the perceived quality of discharge care. In order to achieve these goals, we conducted a prospective cohort study of medical inpatients at a tertiary care hospital in Calgary, Canada. To evaluate patients' perceptions of the discharge care quality, we employed the Care Transitions Measure (CTM). In addition, data were collected from administrative databases to determine the composite outcome of a 90-day hospital readmission or emergency department visit. Logistic regression modeling was used to analyze the relationship between overall CTM scores, individual CTM components, and the composite outcome.

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These studies show that classifiers have the potential to increase prediction accuracy in the healthcare industry. Healthcare professionals can improve patient outcomes and make better decisions by utilising machine learning algorithms and different techniques. Nevertheless, additional study is required to examine classifiers' full potential in healthcare and to solve any possible ethical and privacy issues.

III METHODOLOGY

The dataset in this study is split into two categories, namely training (80%) and testing (20%). The initial proposed model uses KNN to train the training dataset component. To obtain additional features for the original proposed model classifier, RF, SVC, and LR are respectively used for training, requiring a total of 90 fits. A flow diagram of the proposed paradigm is shown in Fig., and it involves three steps. In the first step, the original training dataset is constructed and trained using KNN, RF, SVC, and LR. RF, SVC, and LR are trained on the 80% training dataset. After all four models have been trained in the first step, each model take their self predictions. Subsequently, a new dataset is produced based on the predictions of the fundamental classifiers. The new dataset will have four dimensions. Additionally, this study will analyze and train each of these models separately to evaluate the accuracy and effectiveness of the suggested NN model. Furthermore, the performance of the suggested stacking model will be compared with that of individual classifiers such as KNN, Nave Bayes, Linear Discriminant Analysis, and Decision Tree in terms of Recall, Precision, and F-Measure. Fig. 1 shows the algorithm of the suggested stacking model.

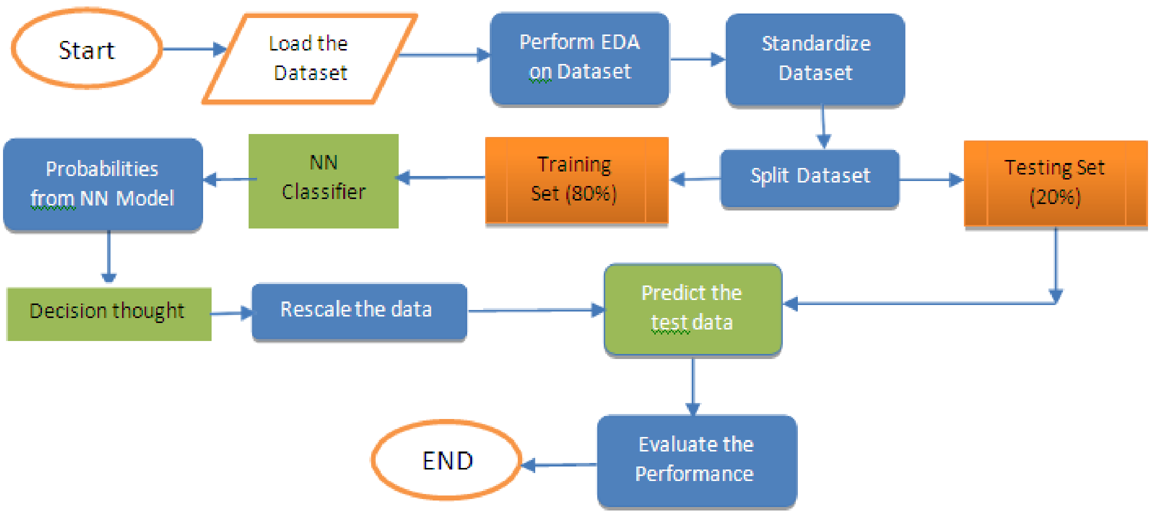

Figure 1 : Flow of process work

To collect the heart disease dataset, we obtained it online from the Machine Learning Repository at the University of California, Irvin. The dataset was then split into training and test sets, and a variety of methods were used to obtain accuracy score results. The study utilized various classification techniques, including Logistic Regression (LR), K-Nearest Neighbor (KNN), Random Forest (RF), and Support Vector Machine (SVM), to identify diseases.

HAEMATO	HAEMOGL	ERYTHROC	LEUCOCYT	THROMBO	MCH	MCHC	MCV	AGE	SEX
35.1	11.8	4.65	6.3	310	25.4	33.6	75.5	1	F
43.5	14.8	5.39	12.7	334	27.5	34	80.7	1	F
33.5	11.3	4.74	13.2	305	23.8	33.7	70.7	1	F
39.1	13.7	4.98	10.5	366	27.5	35	78.5	1	F
30.9	9.9	4.23	22.1	333	23.4	32	73	1	M

34.3	11.6	4.53	6.6	185	25.6	33.8	75.7	1	M
31.1	8.7	5.06	11.1	416	17.2	28	61.5	1	F
40.3	13.3	4.73	8.1	257	28.1	33	85.2	1	F
33.6	11.5	4.54	11.4	262	25.3	34.2	74	1	F
35.4	11.4	4.8	2.6	183	23.8	32.2	73.8	1	F
33.7	11.5	4.57	13.2	322	25.2	34.1	73.7	1	M
54	16.6	7.61	10	88	21.8	30.7	71	1	F

IV EXPERIMENTAL SETUP AND RESULT DISCUSSION

To experiment with heart disease prediction, the spyder scientific programme is used with Anaconda navigator to run Python code with library imports. Hyper parameter adjustment was then used to choose the best characteristics. There were three phases to the experiment.

Stage 1: Basis classifier KNN is employed in the first step.
Step 2: For each of the 30 candidates, the classification methods SVM, LR, and RF were used while fitting 3 folds.
Stage 3: A hyper parameter of 100 epochs is used to specify how many times the learning algorithm will run over the whole training dataset.
Step 4: We have chosen a variety of thresholds for our DSS technique, ranging from 0.1 to 0.65. For each threshold, we verify the precision, recall, accuracy, and f-score using the validation data. To anticipate the test results, the threshold with the greatest performance is ultimately selected.
Step 5: After choosing the expected threshold value, apply it to the patient's data. If the chance of continued care is less than the predicted threshold, the patient may be discharged for our care; if it is higher than the predicted threshold, the patient should not be discharged.

Many common exhibition metrics, such as exactness, correctness, and characterization error, have been taken into account for the calculation of the execution adequacy of models in order to determine the presenting suitability of this model.

Base Algorithm K-NN : Following modelling, we made an effort to illustrate the precision of our approach using the basic classifier's algorithm. Throughout this plotting procedure, it will be determined which basic classifier algorithm will provide the best predictions. The base classifier employed in our investigation generally had the same effect on accuracy. Finding the records that are most similar to another record in terms of shared characteristics is known as K-nearest neighbours.

K-NN Train accuracy: 0.8047605553981297 K-NN Test accuracy: 0.7191392978482446 K-NN Test f-score: 0.6253776435045317

Table 1: Score value on K-NN

	precision	recall	f1-score	support
0	0.74	0.81	0.78	526
1	0.68	0.58	0.63	357
accuracy	-	-	0.72	883
macro avg	0.71	0.70	0.70	883
weighted avg	0.72	0.72	0.71	883

DSS based Neural Network : The majority of the focus that is placed on medical forecasts for the future by ANN-enabled decision support systems (DSS) is directed towards the area of medicine. Because with the help of such a prognosis, a choice on how to care for a sick person may be made in a way that is both speedy and straightforward. It has been suggested that the outcomes of my studies in this area have been favourable, albeit to varying degrees.

Accuracy = 0.7565118912797282

Fscore = 0.696755994358251

Table 2: Score value on optimize neural network

	precision	recall	f1-score	support
0	0.79	0.80	0.80	526
1	0.70	0.69	0.70	357
accuracy	-	-	0.76	883
macro avg	0.75	0.75	0.75	883
weighted avg	0.76	0.76	0.76	883

The line of accuracy for KNN, LR, SVC, and NN is shown in Figure 2, with the KNN model obtaining an accuracy of 71.91%, LR achieving 74.51%, SVC getting 75.19% accuracy, RF achieving 74.40% accuracy, and NN achieving 75.65% accuracy. According to the findings of this research, the proposed NN model, which has an innovative approach to prediction through threshold, performs much better than the various other classifiers.

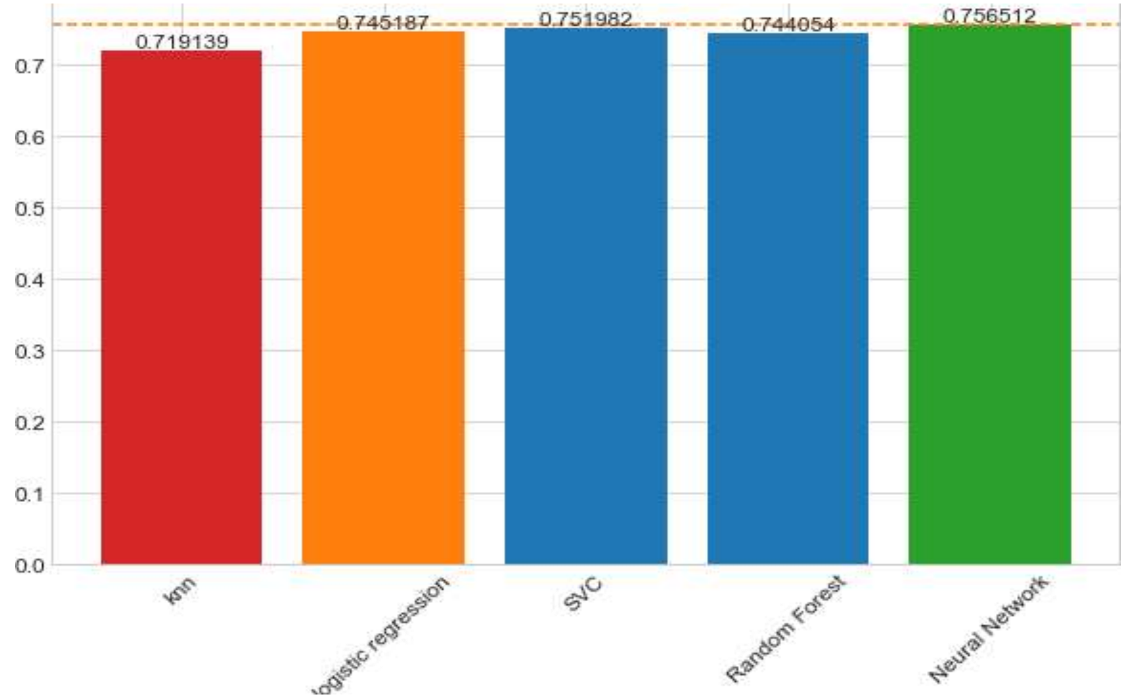

Figure 2 : Accuracy score of All Models

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Table 3: Accuracy comparison table of all models

Model	KNN	LR	SVC	RF	NN
Value in%	71.9	74.5	75.1	74.4	**75.6**

Figure 3 depicts the line of F1 scores achieved by the KNN, LR, SVC, and NN models, with the KNN model achieving 62.53 percent accuracy, the LR model achieving 63.65 percent accuracy, the SVC model achieving 64.84% accuracy, the RF model achieving 64.68% accuracy, and the NN model achieving 69.67 percent accuracy. According to the findings of this research, the proposed NN model, which has an innovative approach to prediction through threshold, performs much better than the various other classifiers.

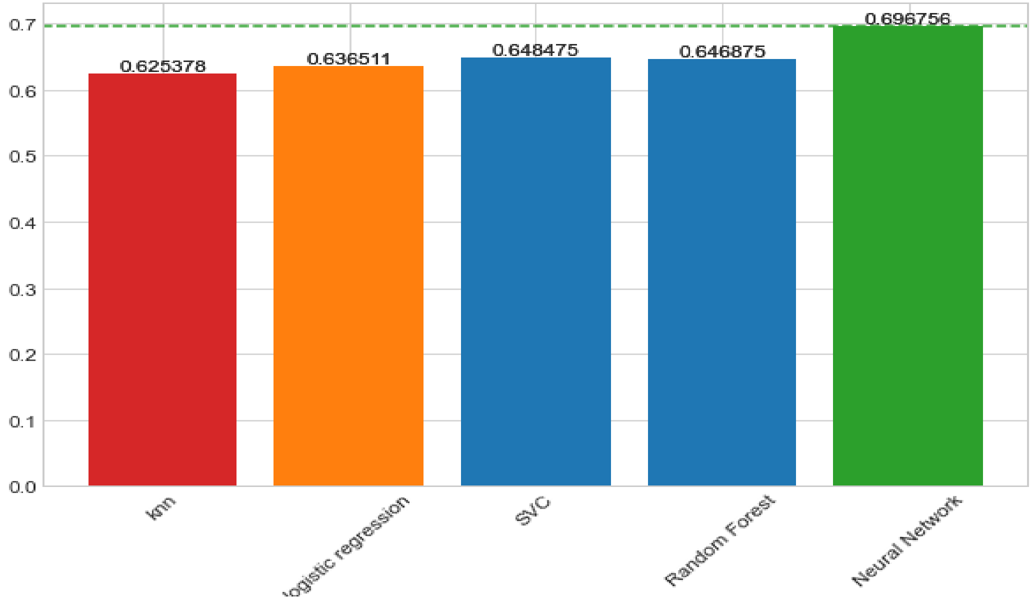

Figure 3 : F1 scores of all models

V CONCLUSION

A novel decision-making classifier model was used in this study to forecast whether patients would be discharged from the hospital or would need to stay. While a lot of work has been done in the past to use classifiers to diagnose illnesses, the prediction of discharge should never be used. In this work, a NN Model is used for classification, with KNN, LF, SVC, and RF classifiers used as comparisons. After evaluating the accuracy, recall, precision, and f-measure, a comparison was made between the NN model and the suggested model. The results of simulations indicate that the suggested model outperforms other existing methods in terms of disease classification and prediction.The main reason the recommended strategy worked so magnificently was because the suggested model used a threshold-based approach that delivered acceptable outcomes.

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