

**A MULTI-LEVEL DECISION-MAKING FRAMEWORK
FOR HEART-RELATED DISEASE PREDICTION
AND RECOMMENDATION**

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Abstract. The precise prediction of health-related issues is a significant challenge in healthcare, with heart-related diseases posing a particularly threatening global health problem. Accurate prediction and recommendation for heart-related diseases are crucial for timely and effective treatment solutions. The primary objective of this study is to develop a classification model capable of accurately identifying heart diseases and providing appropriate recommendations for patients. The proposed system utilizes a multilevel-based classification mechanism employing Support Vector Machines. It aims to categorize heart diseases by analyzing patient's vital parameters. The performance of the proposed model was evaluated by testing it on a dataset containing patient records. The generated recommendations are based on a comprehensive assessment of the severity of clinical features exhibited by patients, including estimating the associated risk of both clinical features and the disease itself. The predictions were evaluated using three metrics: accuracy, specificity, and the receiver operating characteristic curve. The proposed Multilevel Support Vector Machine (MSVM) classification model achieved an accuracy rate of 94.09% in detecting the severity of heart disease. This makes it a valuable tool in the medical field for providing timely diagnosis and treatment recommendations. The proposed model presents a promising approach for accurately predicting heart-related diseases and highlights the potential of soft computing techniques in healthcare. Future research could focus on further enhancing the proposed model's accuracy and applicability.

Keywords: healthcare, heart disease, classification model, learning techniques.

INTRODUCTION

In recent years, a large amount of medical data has become available, representing the healthcare status of patients. This data includes medical reports, test results, and lab reports. Data mining plays a significant role in healthcare recommendation systems, as it enables healthcare professionals to extract valuable insights from the data. These insights can be used to provide more accurate and personalized recommendations to patients [1], [2]. In the current era, people are facing major health issues due to inactive lifestyles. The online healthcare system has proven to be beneficial, especially in scenarios like the COVID-19 pandemic, and has gained significant attention from researchers. Integrating recommender systems into healthcare can support doctors, medical professionals, and patients. These systems assist patients in improving their health conditions and adopting a

healthier lifestyle. Healthcare recommendation systems have evolved with various learning technologies and big data science, which provide online suggestions to patients regarding their health issues.

Machine Learning's application in healthcare is poised to revolutionize the industry, as it enhances capabilities and reduces expenses. This progress empowers healthcare practitioners, including doctors and personnel, to focus more on delivering improved patient care. Many researchers have contributed to healthcare recommendation systems for diagnosing various diseases. Previous studies have employed machine learning classifiers and deep learning techniques to predict different diseases using large datasets gathered from various healthcare repositories.

Recommender systems face various challenges, such as reliability, accuracy, dependability, data loss, and issues related to data integrity and quality. To overcome these challenges, various classification models have been proposed, including the usage of different soft computing techniques like machine learning and deep learning. The significance of this research is to enrich the healthcare dataset for better prediction of multidisciplinary diseases. This study proposes an intelligent disease classification mechanism that aims to address various issues in existing systems by predicting the risks associated with diseases. In this study, a disease classification model is used to predict the risks related to heart conditions. The multi-classification methodology works accurately and provides better results in larger healthcare datasets.

The utilization of the fuzzy technique enables the provision of recommendations to patients based on the severity score. The organization of the paper is as follows: Section 2 reviews recent works in the healthcare recommendation field, Section 3 outlines the research methodology employed in this study, and Section 4 presents the dataset and experimental results. Finally, Section 5 concludes the paper and discusses future plans.

RELATED WORK

Several studies have been conducted on healthcare recommender systems, targeting specific diseases, health-related issues, and recommender contexts. These existing studies have highlighted the need for a comprehensive overview supported by a healthcare recommendation system in various recommendation scenarios. Healthcare recommendation systems offer better personalization, increasing user understanding of their medical conditions [4]. These systems are also concerned with providing accurate information, assisting users, and ensuring the security and privacy of patient information. Traditionally, doctors relied on invasive diagnostic methods to identify heart disease, involving an assessment of the physical examination findings, medical history of patients' and investigation into associated symptoms [5].

Cardiovascular disease, including coronary artery disease, is a major global cause of death, particularly among middle-aged and elderly individuals. Traditional diagnostic methods, such as angiography, are expensive and have notable side effects. To explore alternative approaches, researchers have extensively studied data mining techniques and machine learning techniques. In one proposed work for the accurate diagnosis of coronary heart related disease, the performance of a neural network improved by approximately 10% through the application of genetic algorithms to optimize the network's initial weights [6].

Diagnosing and treating heart disease becomes extremely challenging in underdeveloped countries, where there is a lack of necessary medical tools and specialized professionals [7]. Basic and Deep Neural Networks have shown efficiency in exploratory comparative trials, with the deep neural network outperforming most other methods [8].

Subiksha et al. [9] designed a framework for a medical care system based on machine learning. The framework, based on a decentralized network, was designed to link various healthcare databases and services.

Sahoo et al. [10] developed an advanced prediction model. Their study introduces an intelligent health recommendation system (HRS) that leverages big data analytics to implement an efficient health recommendation engine. The proposed intelligent HRS outperforms existing approaches by achieving a lower mean absolute error (MAE) value, transforming the healthcare industry into a more personalized paradigm within a telehealth environment.

Archenna et al. [11] proposed a methodology for generating a healthcare system. They employed big data analytics in the proposed recommendation system, demonstrating how and where to apply big data technologies to construct an efficient patient recommender system. The study emphasized the need for a system capable of handling massive amounts of semi-structured and unstructured patient information, as well as streaming live information about patients from various social media activities. By utilizing the appropriate machine learning (ML) tools and simulations offered by Apache Spark, useful insights can be derived from vast amounts of medical information. The proposed health recommendation system could anticipate a patient's medical condition by assessing their lifestyle, general medical variables, cognitive medical conditions, and interpersonal networks.

Vanisree K. et al. [12] discuss the significance of an early diagnosis of Congenital Heart Disease (CHD) and propose a Decision Support System to improve accuracy and reduce costs. This system was developed using MATLAB's GUI feature and incorporates a Backpropagation Neural Network.

Abugabah et al. [13] designed a medical care analyzer system based on data mining methodology. In this research work, an optimization-based approach based on neural network was implemented to achieve efficient results. Clinical information was retrieved and normalized using a min-max normalization technique. The patient's condition was examined and categorized as either healthy or unhealthy. The supervised learning approach utilized the harmonic optimized modularity neural network.

Mudaliar et al. [14] developed an application programming interface (API) that utilizes the machine learning algorithms to analyze a user's symptoms and diagnose a specific disease. The framework also recommends suitable drugs for users afflicted with that disease. The prediction of illness probability takes into account externally observable symptoms such as temperature, cough, headache, and other indications experienced by a person. The Naive Bayes algorithm was employed to diagnose the illness based on these signs.

In a study conducted by Yoo et al. [8], a medical care recommendation system based on data mining was developed. The proposed system utilized a peer-to-peer collection and adaptable judgment response. Handheld sensors were employed to gather public health records regarding various aspects of an individual's

life, including nutrition, daily routines, sleeping patterns, lifestyle behaviors, and occupational stress. Validated index data from the P2P-dataset and personal identification were also considered. A mobile service-based medical care recommendation cellular modem could be designed to enhance the quality of care for patient user-based health management, reduce medical costs, and improve service perception of quality in the medicinal industry. Table 1 provides a summary of related work in healthcare recommendation systems.

Based on the literature review, it can be concluded that selecting important features based on studies such as [16–18; 28–31] and employing a combination of classifiers as demonstrated in [16–18; 20; 28–31] can significantly enhance the predictive capabilities of machine learning algorithms for early-stage detection of heart disease. However, feature selection presents a challenge due to the exponential increase in complexity as the number of features in the dataset grows. Evaluating all possible feature subsets becomes computationally intensive and impractical as the number of features increases [32]. Therefore, alternative strategies are necessary to address this issue.

From Table 1, it is evident that only a limited number of research studies have focused on optimizing hyper parameters due to the time-consuming process of tuning multiple machine-learning models to find the best hyper parameters. However, effectively optimizing classifier hyper parameters can greatly improve the accuracy of predicting the risk of coronary heart disease. Healthcare recommendation systems can benefit from the simplicity and accessibility of the multi-class Support Vector Machine (SVM) model, as it has a limited number of hyper parameters for tuning. This characteristic simplifies the training and optimization process. In contrast to more complex machine learning algorithms, the proposed multi classification-based SVM model's straightforwardness makes it a convenient choice for implementation in healthcare recommendation systems.

Table 1. Summary of Related Work

Author References	Proposed Work	Outcomes & Limitations	Scope for future work
Subiksha, et al., [9] (2018)	The deep learning-based health analyzer system. Performance metrics are Precision and Recall	High error rate	Need to enhance the methodology for better results in information retrieval
Sahoo et al., [10] (2019)	Deep learning-based recommendation system for healthcare. Performance metrics are MAE & RMSE	Inefficient privacy results	Need to improve results by resolving security features
Archenna et al., [11] (2017)	Big data-based Healthcare recommendation system The performance metric is accuracy	Security and reliability issues	Need to add security features
Sharma et al., [15] (2017)	Information retrieval approach for healthcare recommendation system. The performance metric is accuracy	Limited features of diseases	Need to add more features of diseases for more efficient results
Shah et al., [16] (2020)	Healthcare system based on the deep learning framework. Performance metrics are Recall, Precision, Accuracy & F-score	Less dataset size	Need to use more datasets for efficient results

Continued Table 1

Author References	Proposed Work	Outcomes & Limitations	Scope for future work
Sornalakshmi et al., [17] (2020)	Healthcare system based on Apriori algorithm. Performance metrics are Accuracy. Execution time	Reliability issues	Need to use different optimization algorithms for efficient results
Gebremeskel et al., [19] (2019)	Dynamic data handling approach. Performance metrics are MAE & RMSE	Anomalies in patient information	Need to overcome anomalies in the patient dataset
Yoo et al., [20] (2019)	Recommendation system based on mining. Performance metrics are Entropy & Gain	Classification issues	Implement enhance feature classification model
Deng et al., [21] (2019)	Collaborative filtering-based Healthcare system. The performance metric is recall	Challenging implementation	Stage analysis on classified data.
Hui Yuan et al., [26] (2018)	A health recommendation system based on hybrid technique. The performance metric is Precision	Offline collected information utilised only	Detect only a few diseases Efficient for small datasets only
Gujar et al., [27] (2018)	Machine learning-based health recommender system. The performance metric is accuracy	Limited dataset	To predict and evaluate the health of real-time cases

PROPOSED METHODOLOGY

In this study, the proposed methodology presents a system consisting of three different levels pertaining to healthcare entities. These levels, namely data collection, data execution, and output, aim to facilitate improved decision-making for doctors and patients. The primary objective of the proposed system is to assist patients in making timely clinical decisions regarding their medical treatment. The various stages involved in the suggested methodology are depicted in Fig. 1. The first step involves pre-processing the patient data to handle outliers and address missing data. Subsequently, the feature selection method is applied to the

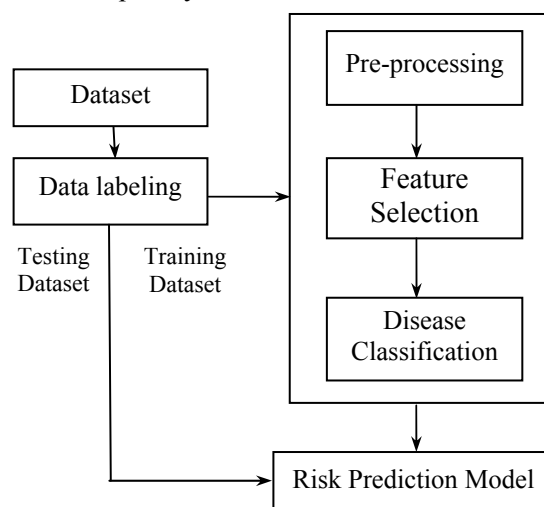


Fig. 1. Architecture for heart disease prediction model

datasets during the classification stage, and the appropriate feature sets are chosen. These selected features are then utilized to predict one of the four predetermined classes of heart disease. The predicted information is subsequently combined with the patient's medical record to offer general medical advice based on the risk level of the disease.

Data Processing

In this phase, data collected from different recourses undergoes a preprocessing phase. Soft computing techniques have become an essential part of meaningful analysis and obtaining optimal results. To improve the training model's performance, we eliminated unnecessary data like missing values, repeating records and outliers. At the top layer, the collected data is initially cleaned and processed, to enhance the presentation and quality of the data used for model development. To identify outliers, missing values, and irrelevant data, we have employed the numerical cleaner filter technique [28]. The processed data was utilized in the feature selection process. Once the data labeling process is completed, the data is subsequently partitioned into two segments: the training dataset and the testing dataset. The training set is utilized for training the classification model, while the testing set is employed to assess the model's performance.

Feature Selection

In the feature selection phase, a subset of highly distinguishing features must be selected for the diagnosis of diseases. In this process discriminating features are selected for different available classes [30]. The datasets used in this study comprise 20 features, among which only a few are pertinent for decision-making in the disease classification process. To reduce the feature vector to a more manageable sample size, a feature selection technique is employed, consisting of two phases.

In the first phase, an attribute selection technique is utilized to evaluate the features present in the datasets. This technique helps assess the relevance and importance of each feature.

In the second phase, we have employed a search technique to select the optimal set of classification models by systematically exploring different combinations of features. The goal is to identify the most effective combination of features that yields the best performance for the classification task. The proposed selection method in this study is information gain-based, wherein the entropy for each class is evaluated [30]. Features that are selected with higher entropy values are more informative and have a greater contribution to the decision-making process. For taking the computing decision selected highest Info Gain is calculated as followed

$$\text{Info Gain}(X) = \text{Info}(Y) - \text{Info}_A(Y),$$

X = Investigation feature; Y = Featured Dataset.

In dataset D to classify a feature Info required which is calculated as

$$\text{Info}(I) = - \sum_{i=1}^n P_i \log_2(P_i),$$

where n = total number of classes; P = probability; D = dataset.

The selection of features based on their information gain is accomplished through an information gain-based technique in this study. This technique is applied using class labels as a basis, followed by a ranker search method. The pur-

pose of this technique is to determine the relevance of features in the classification task and assign them a ranking accordingly.

Prediction

In the next step selected features are classified for the prediction of diseases after being mapped onto the training model. The classification of diseases is structured as a multi-class issue, where patient data is classified into four primary categories, each representing a distinct disease type.

In order to facilitate the training process, we have employed a classification algorithm based on multilevel Support Vector Machine (SVM) in this study. This algorithm functions by utilizing an accurate function and high dimension to separate class data using a hyper-plane. SVM is optimized for multiple classes to deal with real-world issues. In multilevel classification, pair-wise classification of SVM is used to train the given set of data for each pair of given classes.

Once the model is trained, to evaluate the performance and efficiency of the proposed approach we have applied the trained model to the testing dataset. The prediction model results are assessed using three primary metrics, namely accuracy, sensitivity, specificity and ROC, to determine its performance.

Risk prediction and recommendation model for heart disease

The main goal of this study is to develop a recommendation system that can provide accurate recommendations based on the severity of diseases related to heart. The proposed recommendation model evaluates the patient's data to predict the level of risk and determine the severity of the disease. The algorithm for the proposed model is given below:

Input: P = Prediction of Disease, D = Dataset of patients'

Output: Recommendation R : (1, 2, 3, and 4)

(1: No recommendation, 2: Need to normal exercise, 3: Need to visit doctor, 4: Need to get hospitalized and have proper treatment)

1. $X = (x_1, x_2, x_3)$, $\{X$ represent critical feature set}

2. (x_1 : Cholesterol, x_2 : Blood Pressure, x_3 : Blood sugar)

3. $Y = (\text{Critical, Medium, Normal})$ {Let Y represent severity range of X }

4. Let W represent the weight of X

5. $Kb = X, W, Y$ (Kb= Knowledge base)

6. for each disease P and info from k, d

7. Calculate Probability, Prob (P) and Prob (\bar{P})

8. Prob (\bar{P}): occurrence of disease, Prob (P): absence of disease

9. $R = \text{Prob}(\bar{P})/\text{Prob}(P)$ { R =Estimate Risk}

10. If $Y == \text{Critical}$ then,

11. For $R < \text{or} > 1$ AND for Prob $< \text{or} > 0.30$

12. Identify S and compute final score; $\{S = \text{Score}\}$ Final Score = $\sum_{i=1}^m S_i(W_i)$

13. End

14. Else if $Y = \text{medium}$ then,

15. For $R > \text{or} < 1$ AND for prob $< \text{or} > 0.30$ then,

16. FS (Final Score) = $\sum_{i=1}^m S_i(W_i)$

17. End
18. FS (Final Score) = $(0 - 5)$,
19. $0 < FS < 1.9$: $R = 1$
 $2 < FS < 2.9$: $R = 2$
 $2.9 < FS < 3.9$: $R = 3$
 $4 < FS < 5$: $R = 4$
20. End
21. Return R

Recommendation

Scopes of parameters are identified after the prediction of diseases which also depends upon ranges and risk factor values of severity. The four major general types of recommendations assigned to patients are:

1. No recommendation.
2. Normal Exercise.
3. Visit to doctor.
4. Need to get hospitalized.

The range of parameters in the feature set for heart disease is x_1 = Blood Pressure, x_2 : Cholesterol, x_3 : Blood sugar.

The recommendation classes with score ranges and parameters ranges are given in Table 2 and Table 3.

Table 2. Class labels and ranges recommendation

Class	Labels	Scores
Class 1	No recommendation	0–0.25
Class 2	Normal Exercise	0.25–0.50
Class 3	Visit to doctor	0.50–0.75
Class 4	Need to get hospitalized	0.75–1

Table 3. Ranges of parameters to check heart disease

Parameters	Weightage	Ranges	
		Critical	Normal
Blood pressure	0.75	>160	120–160
Cholesterol	0.50	>300	200–300
Blood Sugar	0.25	>125	100–124

RESULT AND ANALYSIS

In the following subsection, we provide details about the dataset used and present the outcomes of the proposed system obtained through experimental evaluation.

Dataset: For our study, we incorporated a heart disease-related dataset. Our developed system was trained and tested on a heart disease dataset that is openly accessible in the UCI library at <http://archive.ics.uci.edu/ml/datasets/heart+disease>. This dataset consists of approximately 1000 patients' health records, with health features described in Table 4.

Table 4. Parameter for the health status of patients

Blood Pressure	
Range of BP (mm Hg)	Risk of disease
90/60 (low)	High
120/80 (Normal)	Fit (No Disease)
140/190 (High)	Very High
Cholesterol	
Range of Cholesterol (mg/dL)	Risk of heart disease
100 to 129 mg/dL	Fit (No Disease)
130 to 159 mg/dL	Border Line
160 to 189 mg/dL	High
190 mg/dL and above	Very High

Output for classification phase

Fig. 2 illustrates the ROC curve representing the performance of the predicted model. The prediction of heart disease achieved an AUC of 0.93 for the MSVM algorithm. The ROC curve of the Random Forest (RF) model is closer to 1, indicating higher accuracy. The curve showcases the pair of specificity and sensitivity values for a specific threshold decision at each point.

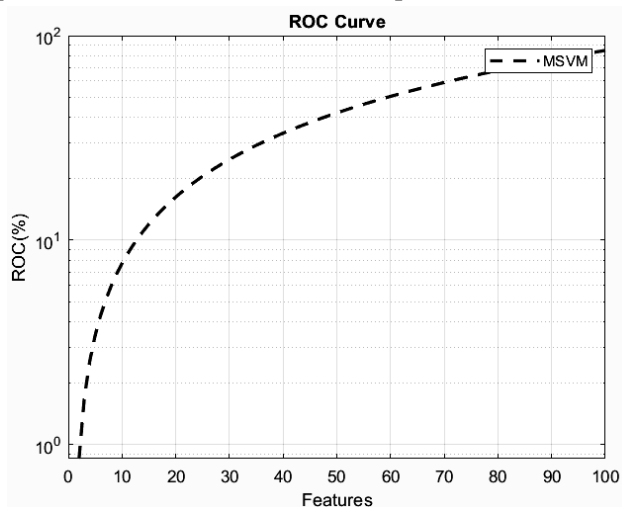


Fig. 2. ROC curve for the prediction algorithm

The performance of the MSVM classifier was evaluated using various performance metrics, primarily accuracy. It was compared to the accuracy of other existing models, namely KNN (85.1%), Naïve Bayes (89.7%), and neural network (91.8%). KNN relied on a single parameter, K (number of neighbours), while Naive Bayes utilized two hyperparameters, α and β , for features classification. The neural network employed the sigmoid activation function to optimize parameters [33].

Fig. 3 presents a curve that represents the accuracy of the multilevel Support Vector Machine (MSVM) classification model. The model achieved an accuracy rate of 94.09%, indicating an optimal solution for improving accuracy compared to existing models such as KNN, Naïve Bayes, and neural network, as shown in Figs. 4, 5 and 6 display the specificity and sensitivity rates, respectively. These

figures provide insights into the model’s performance in terms of correctly identifying true negatives (specificity) and true positives (sensitivity).

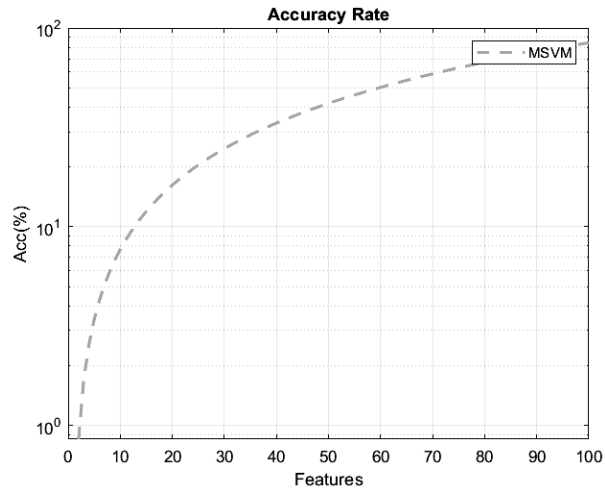


Fig. 3. Accuracy curve for the prediction algorithm

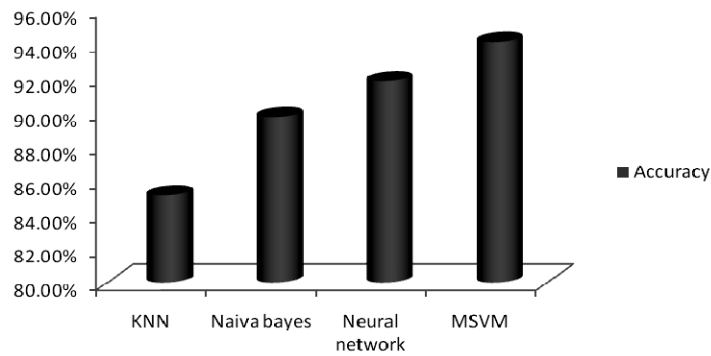


Fig. 4. The Accuracy of different algorithms

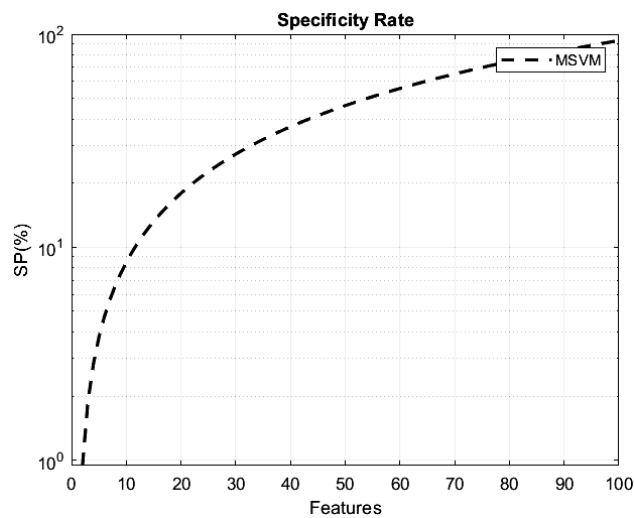


Fig. 5. Specificity Rate

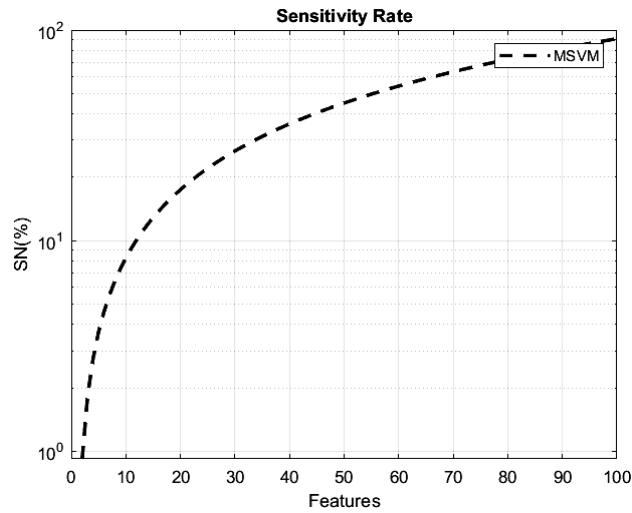


Fig. 6. Sensitivity Rate

The output of the prediction and recommendation phase

In this section, outcome from the prediction and recommendation phase is presented. This research work aims to predict health-related issues in patients and provide recommendations based on the risk and probability of occurrence of diseases. Initially, knowledge is gathered from medical experts and clinical records, and then the weight of each parameter is applied based on its significance. Based on the criticality of parameters different ranges are assigned. Parameters falling in the normal category are ignored.

The following equation is used to evaluate the risk based on the knowledge base database:

$$\text{Risk } (R) = P(e)/P(e);$$

$P(e)$ = Probability of disease with abnormality;

$P(e)$ = Probability of disease without abnormality.

The prediction of the diagnosed disease likelihood is based on the input from the fuzzy system and the classification process and determines the corresponding risk level. By analyzing the given dataset using this method, the resulting values indicate whether the patient’s health is at risk or not. The output obtained from the fuzzy model can be found in Table 5.

Table 5. Sample table of outputs of recommendation model

Patient id	Disease	Level	Recommendation
51	Normal	0	No recommendation
57	Heart disease	0.25	Normal Exercise
63	Normal	0	No recommendation
75	Critical Heart disease	0.5	Visit to doctor
81	Highly Emergency	1	Need to get hospitalized

CONCLUSION & FUTURE WORK

The study proposes a framework for predicting and recommending treatments for heart-related diseases using a multilevel decision-making approach. The proposed

multilevel classification model, based on the support vector machine, achieves an accuracy rate of 94.09% and provides crucial health recommendations for the early prevention of critical diseases to patients upon disease detection. Implementing these recommendations can help reduce the risk of heart disease and ensure better health outcomes for patients.

In the proposed work, a dataset of around 1000 patients was used. However, it should be noted that the proposed model has limitations, as it relies on clinical validations for any health recommendation decisions.

The proposed model contributes to the medical field by enabling better decision-making for patient healthcare. The analysis of the results focused on accuracy, and we compared the accuracy of our proposed model with three commonly used algorithms (KNN, Naïve Bayes, and Neural Network). We found that the MSVM classification algorithm provided the optimal solution with better accuracy.

In future research, the suggested approach will be evaluated using a real-time dataset. Additionally, the scheme can be expanded by examining the influence of additional characteristics on the recommendation of heart disease, thereby enhancing safety during the validation stage. To achieve this, the implementation of deep learning based technology is necessary. This technology will enable visualization and recording of the learning process, ensuring transparency in the use of deep learning-based techniques.

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БАГАТОРІВНЕВА СИСТЕМА ПРИЙНЯТТЯ РІШЕНЬ ДЛЯ ПРОГНОЗУВАННЯ ТА РЕКОМЕНДАЦІЙ ЩОДО ЗАХВОРЮВАНЬ, ПОВ'ЯЗАНИХ ІЗ СЕРЦЕМ / Vedna Sharma, Surender Singh Samant

Анотація. Точне прогнозування проблем, пов'язаних зі здоров'ям, є серйозною проблемою в галузі охорони здоров'я, причому серцево-судинні захворювання становлять особливо загрозу в глобальній проблемі охорони здоров'я. Точне прогнозування та рекомендації щодо серцево-судинних захворювань мають вирішальне значення для надання своєчасного та ефективного лікування. Основною метою цього дослідження є розроблення моделі класифікації, здатної точно ідентифікувати захворювання серця та надати відповідні рекомендації для пацієнтів. Запропоновано систему, яка застосовує багаторівневий механізм класифікації з використанням опорних векторних машин. Він спрямований на класифікацію захворювань серця шляхом аналізу життєво важливих параметрів пацієнта. Ефективність запропонованої моделі оцінено шляхом її тестуванням на наборі даних, який містить записи пацієнтів. Сформовані рекомендації ґрунтуються на всебічному оцінюванні тяжкості клінічних проявів, які демонструють пацієнти, включно з пов'язаним ризиком як клінічних ознак, так і самого захворювання. Прогнози оцінено за трьома показниками: точність, специфічність і крива робочих характеристик приймача. Запропонована модель класифікації Multilevel Support Vector Machine (MSVM) досягла рівня точності 94,09% у виявленні тяжкості серцевих захворювань, що робить її цінним інструментом у галузі медицини для надання своєчасної діагностики та рекомендацій щодо лікування. Запропонована модель дає багатообіцяльний підхід для точного прогнозування захворювань, пов'язаних із серцем, і засвідчує потенціал методів програмного обчислення в сфері охорони здоров'я. Подальші дослідження можна зосередити на удосконаленні підвищення точності та застосовності запропонованої моделі.

Ключові слова: охорона здоров'я, захворювання серця, модель класифікації, методи навчання.