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DESIGN AND ANALYSIS OF RANDOM FOREST ON RESOURCE OPTIMIZATION INTELLIGENT IOT SYSTEMS IN HEALTHCARE INDUSTRIAL ENVIRONMENTS

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Abstract:
Aim/Scope: Emphasizing Intelligent Internet of Things (IoT) Systems notably, the paper evaluates the Random Forest algorithm in resource optimization in industrial settings related to healthcare. This project aims to improve the administration of data and the decision-making process in healthcare contexts by means of design, implementation, and analysis of an RF algorithm.
Background: For real-time patient data collecting from many sites, IoT sensors and devices are growing in importance for healthcare systems. However, given its volume, variety, and speed, efficiently digesting this data and getting important insights creates challenges. Among other machine learning methods, Random Forest offers potential strategies for best use of resources and improvement of healthcare decision-making processes.
Methodology: Compiling patient data from home, laboratory, clinic, remote location using IoT sensors from many sources. Data computation and categorization follow from Random Forest then. Experimental evaluations make use of several disease sets obtained from credible sources.
Contribution: IoT is a network design allowing billions of physical objects to be connected to the internet and data sharing among themselves. This relates to the software as well as the numerous sensors forming the Internet of Things. Devices—physical as well as mobile ones and other types—are able to interact with one another using wireless communication technology. For data processing and classification needs, the Random Forest approach follows afterward. Experimental evaluations make advantage of a wide spectrum of disease datasets obtained from reliable sources.

Findings: Compared to other classification methods, such Decision Tree, which produces motivating accuracy, sensitivity, and specificity. The results of the conducted out experiments confirm this.
Recommendations for Researchers: Future avenues of research could involve looking at the scalability and applicability of the Random Forest algorithm in different and diversified bigger healthcare systems and environs. Moreover, looking at ensemble methods and hybrid approaches combining RF algorithm can help to improve its performance and utilization in industrial environments related to healthcare. Moreover, the investigation of the effects of the RF algorithm on patient outcomes, cost-effectiveness, and resource use would give medical practitioners perceptive understanding.
Future Research: In future research, this work can be enhanced using several deep learning algorithms integrated with IoT technology for achieving better accuracy and performance.

Keywords: Random forest, IoT, cloud, patient, healthcare, Industrial

INTRODUCTION

Two areas where current technology—including Healthcare 4.0—may come across challenges are data security and privacy. For these technologies, these obstacles can so slow down their adoption pace. Protection of user data—which might include personal information about patients or service users—is of utmost relevance (Khan et al., 2022; Tabaie et al., 2021; Bhende et al., 2022). Medical records, user genetic codes, identifying information, and a lot of other sensitive records are among the broad spectrum of delicate data kept in the database. One should also consider the fact that this idea lacks standards, which makes interaction with other systems difficult. Standardizing procedures helps healthcare providers improve data interchange between different device tiers and enable greater sharing of resources.
Mostly grounded in real-time information availability, the Healthcare 4.0 idea greatly affects sustainability (Khan et al., 2022). Faster and more efficient replies from doctors and nurses made possible by this concept are expected to help to enable more accurate patient diagnosis. Medical staff members always have simple access to information confirming the patient's current condition. One should underline the opportunity to track significant patient parameters in real time (Govindan et al., 2022). The doctor and the other members of the medical staff could be able to adjust the therapy plan as soon as the patient's condition deviates from the previously stated parameters. Healthcare 4.0 also enables the quick identification of significant medical events, including a patient experiencing a heart attack, therefore simplifying and accelerating the process. These kinds of situations call for the necessary activities to help the patient to live. Sometimes referred to as Healthcare 4.0, the technology has the ability to increase involvement with pertinent medical institutions by streamlining contacts with doctors practicing relevant medical disciplines. Real-time diagnostics so enable and quickens the process of making medical decisions (Shesayar et al., 2023). Like in other fields, Healthcare 4.0 influences other elements as well as sustainable cities. The optimization of pathways determines the availability of sustainable health care, so it is related with concepts like smart cities and sustainable transportation. IoT is a network design enabling billions of physical objects to connect to the internet and communicate data among themselves. This relates to the software as well as the numerous sensors forming the Internet of Things. Devices—physical as well as mobile ones and other types—are able to interact with one another using wireless communication technology. The IoTs significantly help to enhance models of healthcare.

RELATED WORKS

The author of (Wu et al., 2019; Perveen et al., 2016; Sisodia & Sisodia, 2018; Shankar et al., 2020) proposed several methods including Radiological fuzzy logic (RF), neural networks (NB), artificial neural networks (ANN), and linear regression on evaluating the probabilities of liver disease across a large dataset.
Designed for usage in patient hepatitis prediction, Parisi et al. ((Parisi et al., 2020) developed a hybrid model. Using multilayer perceptrons (MLP) and lagrangian support vector machines (SVM), the model labeled the data as hepatitis. For the area under the curve measure as well as for accuracy, the model performed satisfactorially. The researchers (Kumar & Vigneswari, 2019) created a prediction mechanism. This prediction system was supposed to help the study aiming at hepatitis incidence forecast.
Vijayarani and Dhayanand (Vijayarani & Dhayanand, 2015) develop a model to predict the renal disease using SVM and NB techniques. Also in the work (Hameed et al., 2015) same pattern of prediction mechanism has been suggested and they achieved outstanding level of accuracy.

Besides that, our method uses better class outlier detection. Jahangir et al.(Jahangir et al., 2017) developed a diabetes prediction method they called Auto MLP; the parameters are automatically adjusted while the training is still under way.
Harimoorthy and Thangavelu (Harimoorthy & Thangavelu, 2021) developed a model capable of predicting several diseases, including kidney disease, diabetes, and cardiovascular disease. They succeeded with multiple different machine learning classifiers. Accurate diagnosis was made using the present method for 89.9% of patients with heart disease, 98.7% of diabetic sufferers, and 98.3% of renal disease sufferers overall (Haq et al., 2018).
Aimed at predicting cardiovascular disease occurrence, Amin et al. [19] developed a hybrid intelligent healthcare model. Performance of machine learning classifiers was enhanced using three feature selection methods: mRMR, Relief, and Lasso. The created model using logistic regression had an accuracy of 89%; the accuracy using support vector machine training was 88%.
To find the risk factor, Verma et al. (Verma et al., 3016) first presented the computer-aided design (CAD) approach utilizing the K-means and particle swarm algorithms. Among the methods of learning applied for data extraction were a multilayer logistic regression (MLR); a fuzzy unordered rule induction method, C4.5; and a multilayer perceptron (MLP). There are 335 samples in this collection, and among them there are 26 properties overall. According to the study, MLR attained the maximum degree of accuracy—that is, 88.4 percent.
Alkeshuosh et al.'s (Alkeshuosh et al., 2017) examination on the condition of cardiac illness using current diagnostics was successful in generally getting an accuracy rate of 87%. Using Lasso SVM classifiers, Muhammad et al.'s (Muhammad et al., 2020) built healthcare model. This model aims to early and exactly predict the development of cardiac disease. Our degree of accuracy with this model was 94.41%. Samuel et al. (Samuel et al., 2017) put up a model for heart failure prediction; the accuracy of their model came out to be 91.10%.
(Khourdifi & Bahaj, 2019) aimed to provide a paradigm for Parkinson's disease prediction. Applying the SVM classification method, they correctly forecast the disease. The use of artificial intelligence reported by Mathur et al. (Mathur et al., 2020) was meant to provide projections concerning the incidence of cardiovascular disease. They also offer a reason for why early diagnosis of cardiovascular disease rely particularly on ML methods. The authors provide evidence connecting cardiovascular illness, machine learning, and artificial intelligence. Zou et al. (Zou et al., 2018) focused on the implementation of machine learning techniques aiming at diabetes mellitus prediction. On 689,994 data points total, we conducted this study using RF, J48, and neural network methods. These data points were equally distributed in the populations of diabetes and healthy individuals. Among the numerous considerations, radio frequency (RF) has turned out to be the preferable choice.

METHODS

IoT is a network design allowing billions of physical devices to be connected to the internet and data sharing among themselves. This relates to the software as well as the numerous sensors forming the Internet of Things. Devices—physical as well as mobile ones and other types—are able to interact with one another using wireless communication technology. The IoTs significantly help to enhance models of healthcare. By means of a range of sensors, both within and outside the body, one can get data from particular people. While surgically implanted sensors acquire data from within the body, the eternal sensor gathers data from the outside world and surrounds. Medical professionals use gathered data to project diseases. The developed model divides the data into healthy and sick groups using many machine learning classification methods. Early stage disease can be exactly identified using machine learning-based classifiers. Inside the framework of the proposed paradigm, the IoTs have been taken advantage of.
Patients in this data collecting are employing commonly available and reasonably cheap IoTs (IoT) devices personally. Following data collecting, these IoTs convey patient health information.
In this situation, the patient attends a laboratory or clinic but no accompanying physician is ready to give them test results or clinical patient data. This is true even with every required instrument easily available. The medical support team handled patient data collecting in past years.
In a physical sense, some people can be living distant from hospitals. This information relates to patients discovered at distances. IoT-connected gadgets compile patient information and deliver it directly to clinicians so they could enhance their treatment strategies. Defining the data set are conditions including cardiovascular disease, diabetes, hepatitis, dermatology, thyroid, breast cancer, and liver diseases.
Figure 1 presents a concept of the desired architecture. The proposed paradigm assigns artificial intelligence and the Internet of Things a great relevance. First under consideration is the IoT, which ties everything to the internet. Real time patient data is gathered and subsequently forwarded to the care provider. Lag is not produced in data processing. The second parameter is artificial intelligence (AI); it examines acquired data and, following

processing, quickly provides results. The IoTs and artificial intelligence provide effective data management on massive volumes.

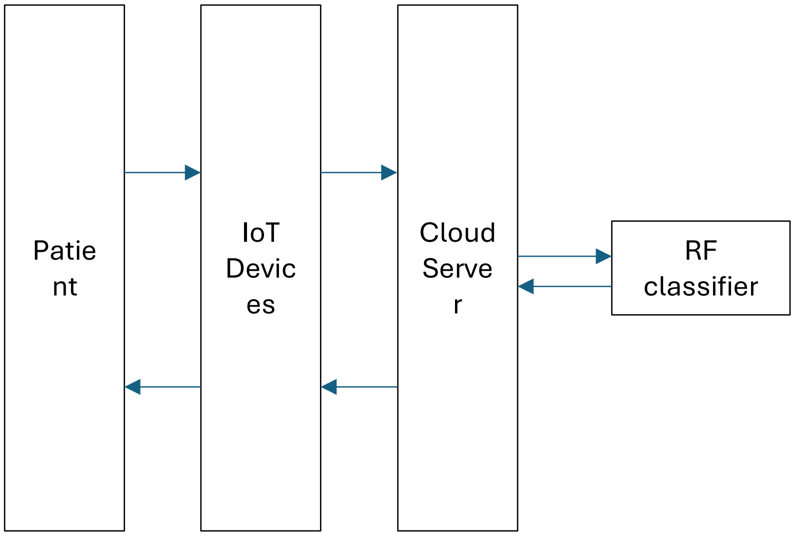

Figure 1: Proposed Architecture

There are three primary steps that bring the project to end. Data collecting, pre-processing and data crunching form three processes; the results are easily available to end users or doctors kept on a cloud server.

Data collection

From numerous sources—including their residences, labs, clinics, and even distant databases—information about patients is compiled in this section. Real-time patient data is obtained by means of several sensors and devices connected to the IoTs. The houses of those who live regularly fit with the required sensors. The lab technicians have to provide clinical and lab data and engage with the IoTs agent. Those patients who reside far apart have multiple separate sensors implanted in their bodies. The agent in charge of the IoTs receives the gathered data from these sensors later on.

Pre-processing

Part of the pre-processing procedure is a missing value search and filtering of the acquired data. The data is sent to a cloud able of computation after the pre-processing phase finishes. This particular case computes and groups the data using DT.

Decision Tree (DT)

These three independent traits assist us to assess the conditional probability. The leaf nodes, who are at the very top of the tree, are in responsible of assigning classes while the branch nodes, who are found farther down the tree, make choices on the tests. DT nodes not specifically declared as leaves represent tests. The decision tree method calls for no specific information relevant to a domain. Numerical and categorical data management and understanding were greatly simplified to aggravate the situation. On the other hand, depend on the dataset and the performance is limited to one output property.

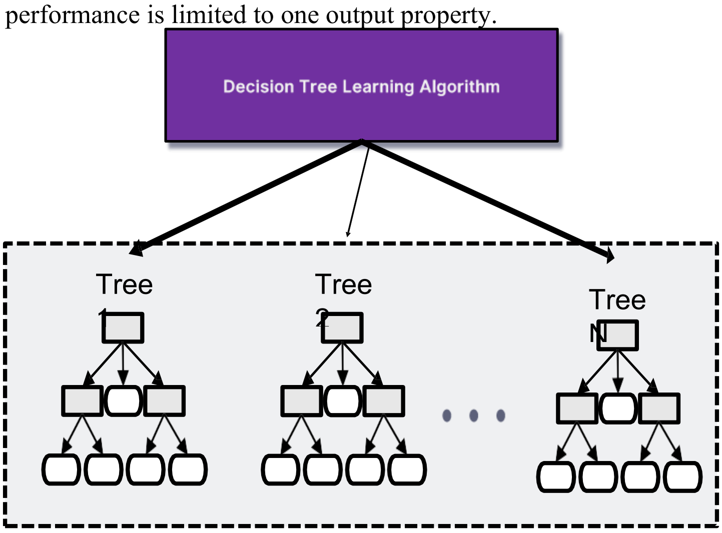

Figure 2: Random Forest classifier

Among the various classification jobs machine learning can handle, Random Forest is a powerful ensemble learning technique special in character. Learning proceeds with the construction of a network of decision trees during the training phase then with the use of the average prediction or mode of classes obtained from that network. The Random Forest classifier comprises, enumerated above, the following methods:

1. Bootstrap Sampling: Sometimes known as Random Forest with Replacement, the Bootstrap Sampling approach is a method whereby some of the original data is utilized to train extra decision trees.
2. Feature Randomization: Apart from choosing data point samples, the Random Forest technique generates features randomly. It selects at random a subset of features instead of the complete set under investigation at every decision tree node to divide.
3. Growing Decision Trees: The third is building a recursive sense decision tree for every bootstraps sample is doable.
4. Voting or Averaging: Voting or averaging therefore indicates that every tree " votes" for the class label of the input sample, thus the class chosen as the forecast class is the one with the most votes. Usually, one gets the final estimate by averaging the forecasts produced by the several trees involved in a regression study.
5. Evaluation and Tuning: Either cross-validation or a separate validation set analyzes the Random Forest model after the training stage. This is done in search of its efficiency. By use of grid search or random search, hyperparameters including the forest size, maximum tree depth, and minimum samples per leaf node may be fine-tuned so optimizing the performance of the model and preventing overfitting.
6. Prediction: After training and Random Forest classifier testing, one can create forecasts based on totally new data not seen before. Every single decision tree housed inside the forest passes the input sample through to ensure the accuracy of the forecasts produced even in circumstances of noisy or incorrect data.

Performance

This paper investigates the outcomes of numerous different classification techniques. From diabetes, cardiovascular disease, Hepatitis, breast cancer, dermatology, liver illnesses, thyroid, surgery, and spect heart, our team has used a broad array of disease datasets. Table 1 lists the dataset used coupled with several samples; the repository from which this dataset was acquired is "https:// Archive.ics.uci.edu/ml/datasets.php." Python was the programming language I used for implementation using a 2.80 GHz Intel Core i7 CPU M60. Twenty percent and eighty percent of the dataset are reserved only for experimentation. While testing makes advantage of twenty percent of the dataset, the training of classification algorithms makes advantage of eighty percent of the dataset.

Table 1 Experimental work dataset

Dataset	No. of class	No. of instances
Breast cancer	2	557
Diabetics	2	611
Heart disease	5	241
Liver disorder	2	275
Hepatitis	2	123
Surgery data	2	374
Thyroid	6	7303
Dermatology	6	291
Spect heart	2	149

Table 2: Accuracy of the seven classifiers

Data set	Training	Testing	Validation
Heart disease	88.33	89.40	91.21
Diabetics	86.24	91.24	90.77
Breast cancer	91.82	94.15	93.83
Hepatitis	90.34	94.57	94.13
Liver disorder	69.30	75.24	72.63
Dermatology	87.58	94.03	94.74
Surgery data	82.39	88.29	87.23
Thyroid	80.39	82.46	82.56
Spect heart	79.59	81.76	82.40

Four machine learning classifiers whose performance these results highlight are Support Vector Machine (SVM), K-Nearest Neighbours (KNN), Artificial Neural Network (ANN), and Random Forest. Accuracy, precision, recall, F1-score, and classification error are the evaluation criteria applied to contrast several classifiers.

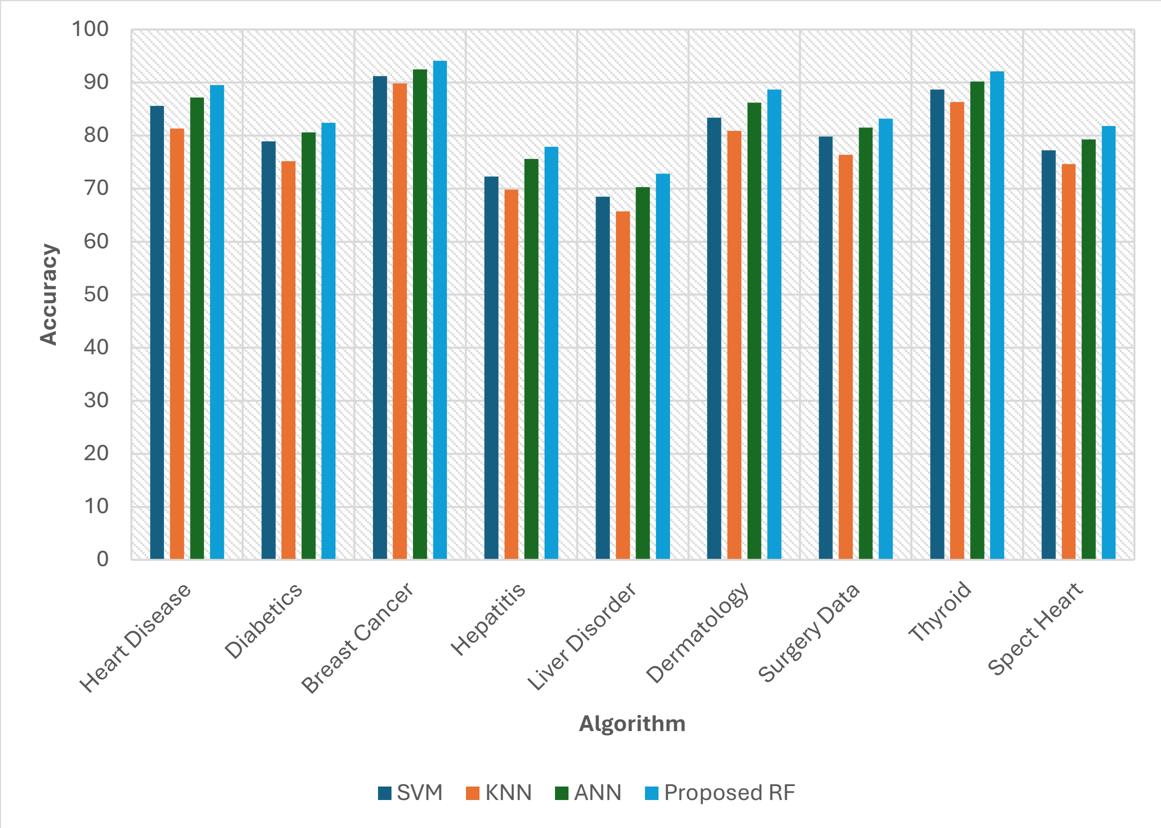

Figure 3: Accuracy

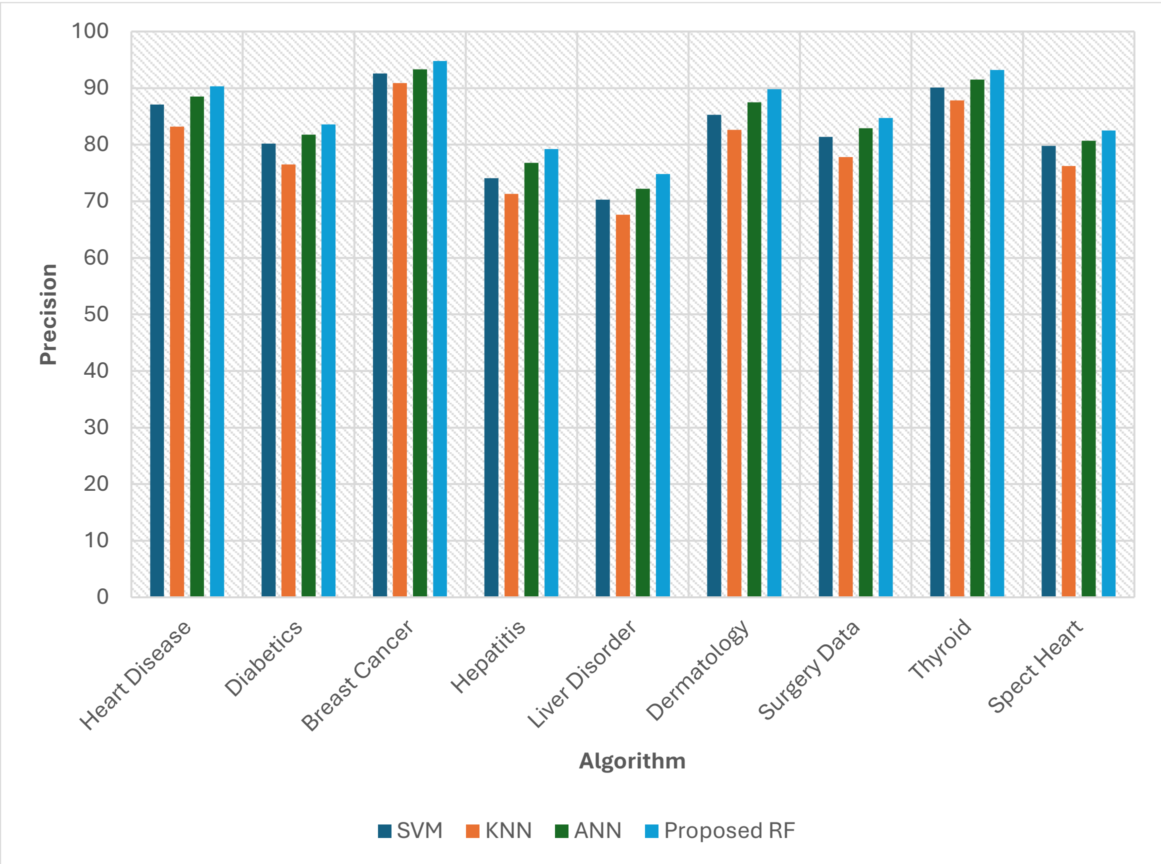

Figure 4: Precision

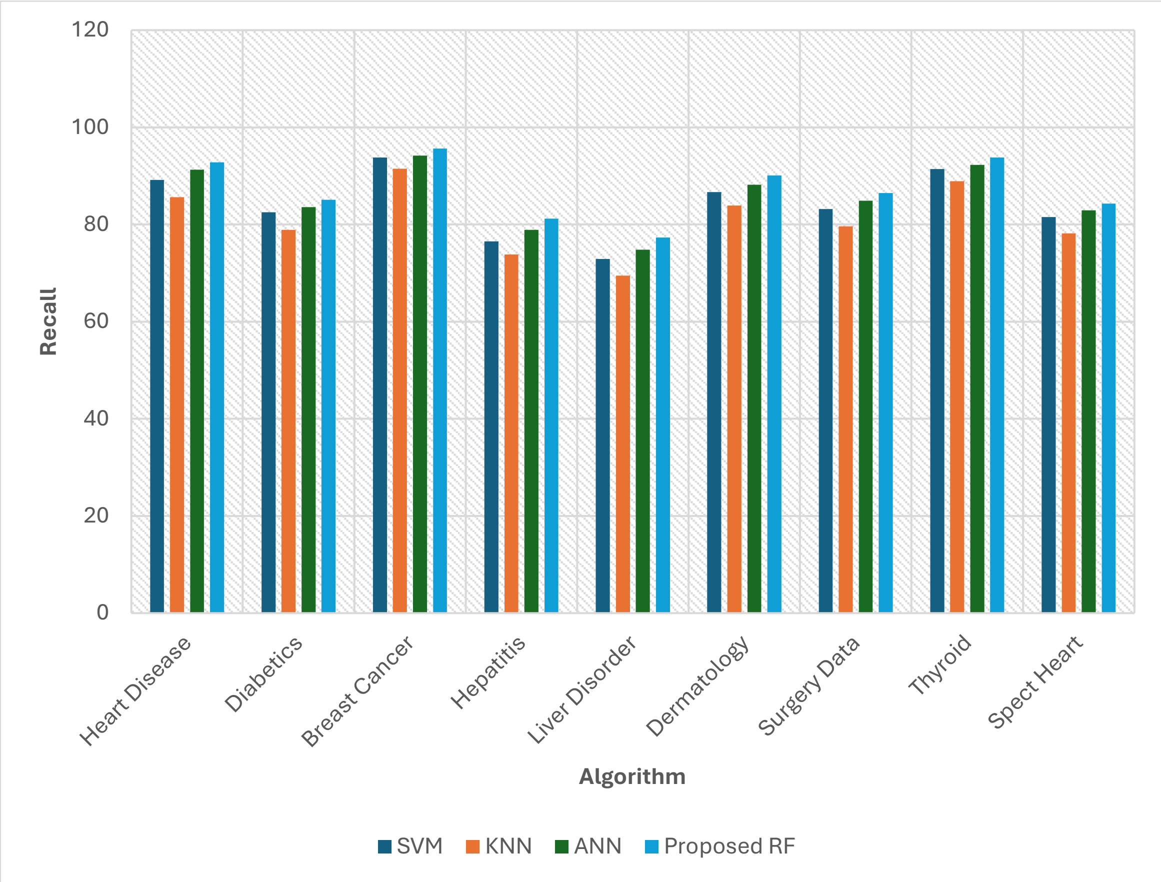

Figure 5: Recall

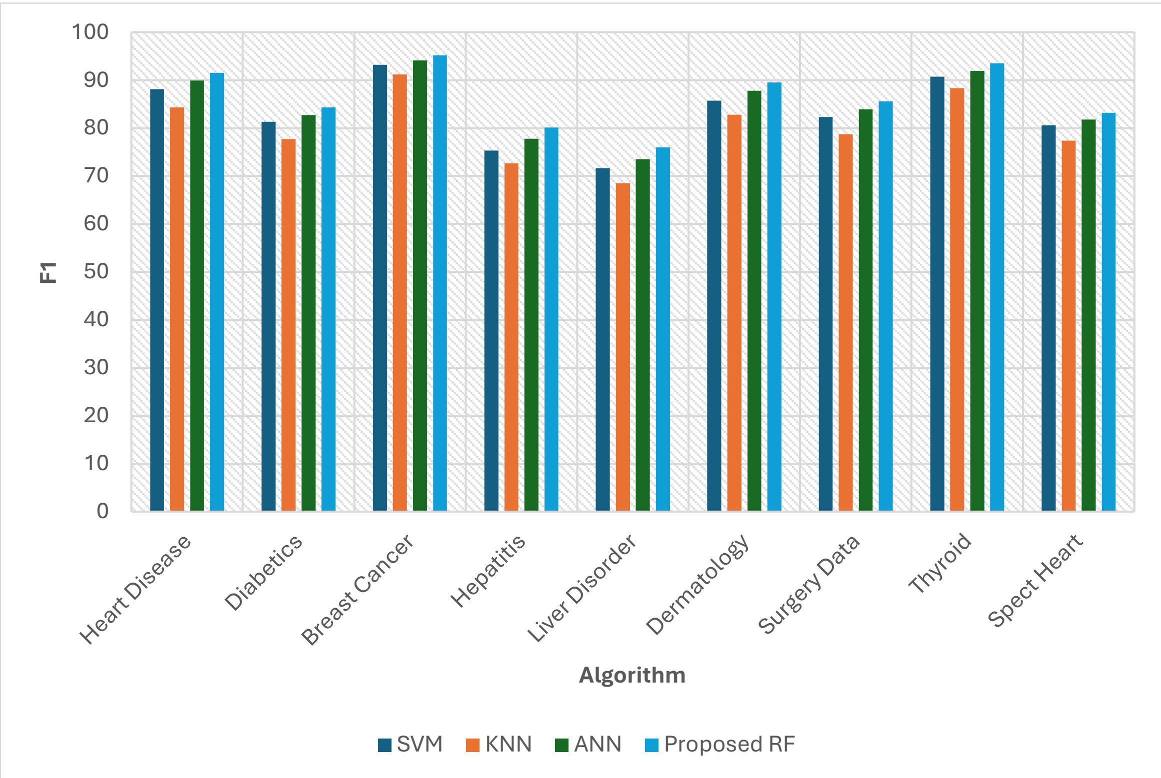

Figure 6: F1-score

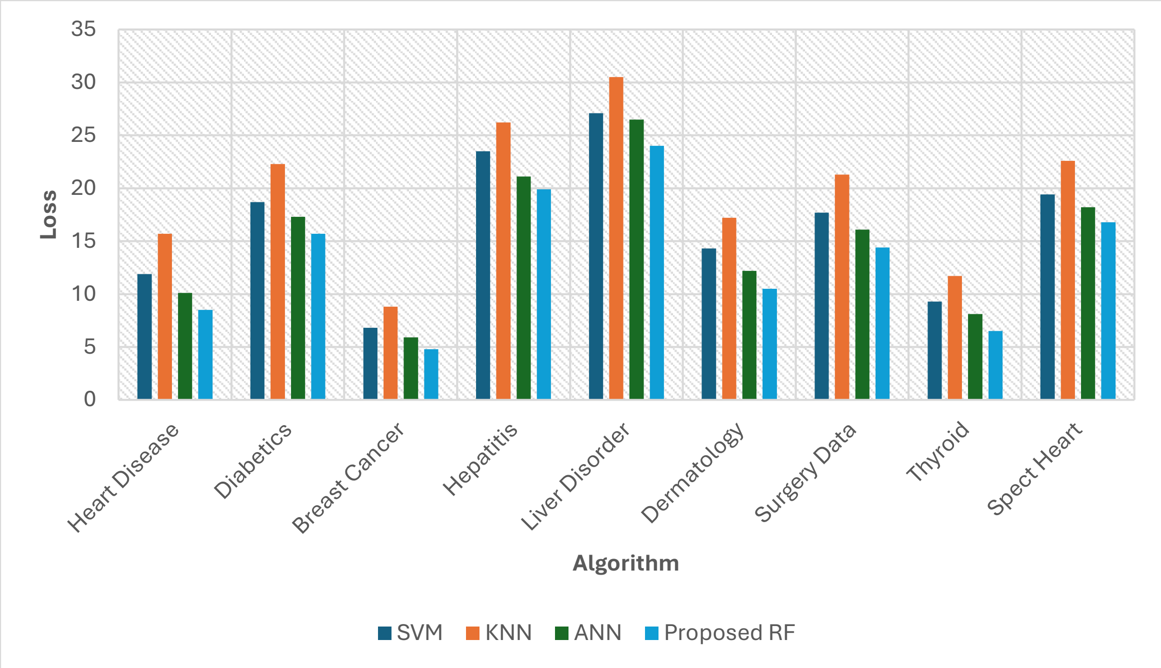

Figure 7: Classification loss

From the full dataset, the accuracy shown in Figure 3 gauges the fraction of correctly diagnosed cases. In medical diagnostics, "accuracy" is the degree to which a classifier can accurately project the sick status. Since the Random Forest classifier regularly demonstrates the best accuracy for most of the diseases, it is obviously helpful in correctly identifying medical data. With accuracy of 94.1% for breast cancer and 89.5% for heart disease, it beats the other classifiers in both respects.
Figure 4 displays the accuracy of the classifier by computing the percentage of true positive predictions inside the total count of positive predictions produced by it. Apart from other current approaches, the proposed method delivers 94.8% of accuracy score and produces superior result on false positive predictions.
More than any other present method, the proposed one displays 95% of accuracy in Figure 5 and achieves higher recall rate. Represented in Figure 6, the F1-score fairly evaluates the performance of a classifier. Figure 7 shows the classification error rate, therefore indicating the percentage of dataset cases misclassified. Reducing the classification error rate shows the classifier under current use is getting better.

CONCLUSION

The results reveal the effectiveness of four various machine learning classifiers for a wide range of diseases. With accuracy of 94.1% for breast cancer and 89.5% for heart disease, it beats the other classifiers. In medical diagnosis, the capacity of the classifier to eliminate false positives is vital since it helps to avoid erroneous diagnosis. The classifier generates this information. Once more as shown, the Random Forest classifier exhibits outstanding accuracy scores for several illnesses, including breast cancer (94.8% of cases) and heart disease (90.3% of cases), hence helping to reduce the false positive prediction count.
Future directions of study could be looking at the scalability and applicability of the Random Forest algorithm in heterogeneous and diversified larger healthcare systems and environs. Moreover, looking at ensemble methods and hybrid approaches combining RF algorithm can help to improve its performance and utilization in industrial environments related to healthcare. Moreover, the investigation of the effects of the RF algorithm on patient outcomes, cost-effectiveness, and resource use would give medical practitioners perceptive understanding.

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