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Enhancing Predictive Accuracy in Healthcare: A Comparative Analysis of Machine Learning Models for Disease Diagnosis

Ajoy Roy[1], Simanto Podder[2], Effat Ara Tanzin[3], Rukaiya Islam[4]

[1,2,3,4] **American International University-Bangladesh**

ABSTRACT

This sets the background for an exponential rise in healthcare data, consequently aiding in harnessing the power of machine learning models toward better diagnosis of diseases. In this paper, we make a comparative analysis between different machine learning techniques, such as decision trees, neural networks, and random forests, toward enhancing predictive accuracy in healthcare diagnostics. We analyze multiple attribute-based patient data sets and find the effectiveness of each model in diagnosis with high precision. Evaluation criteria are accuracy, precision, recall, and F1-score for the model; computational efficiency is also evaluated. We show that, although neural networks are more accurate on complex and nonlinear relationships, random forests provide balanced performance across all metrics and thus could be suitable for general-purpose diagnostics. Decision trees, though less accurate, offer valuable interpretability that is very useful to medical practitioners. It highlights the need for relevant machine learning models targeted at specific applications in healthcare for further improvement in diagnostic accuracy and support for the clinical decision-making process. Further research in this area can involve merging these models with patient data in real-time to increase their utility in these dynamic health environments.

Keywords: Machine Learning, Disease Diagnosis, Predictive Accuracy, Neural Networks, Random Forests

1. INTRODUCTION

Machine learning has grown as a potential technology applied by many different industries, excluding health, for the betterment of diagnosis and treatment. The outlook for machine learning in healthcare is particularly brilliant since it can run through bulk volumes of data to reveal patterns invisible to the human eye [1]. Challenge: With the growing size and complexity of healthcare datasets, handling this data is but a part of the problem; how meaningful insights are derived is one of the questions that will eventually prove key to better patient outcomes [2].

One of the major machine learning applications in healthcare is disease diagnosis. Diagnosis forms the basis of the treatment and management of diseases. Therefore, it has to be very accurate. Traditional diagnostic methods, which are greatly dependent on manual analysis and heuristic rules, are inadequate for the complex and high-dimension nature of medical data. Machine learning models are the solution since they can automate and improve the diagnostic process with very advanced algorithms for detecting the slightest trends and relationships between data [3].

In the past few years, several machine learning models have been explored in disease diagnosis, all with their strengths and weaknesses. DTs are among the simplest yet very powerful models. DT works by recursively partitioning a feature space in a way conceptually like a tree-like structure; here, every node designates features, with every branch representing a decision rule [4]. Though simple to use, DTs can be very prone to overfitting, consequently affecting their generalization performance [5].

Another ensemble method that could help overcome some of these limitations is RF, based on DTs. RFs build a lot of decision trees and aggregate their predictions to get better accuracy and robustness for their predictions [6]. In this way, it will be less prone to overfitting issues and have better generalization capability on unknown data. RF has often been shown to perform better than single DTs in different diagnostic tasks [7].

The more complex approach includes neural networks, especially deep learning models. NNs can handle intricate patterns and features from raw data by conducting multiple layers of processing. NNs are capable of handling large datasets with high-dimensional features for disease diagnosis and return predictions with higher accuracy [8]. Nevertheless, these techniques often require a large amount of computational resources and careful tuning to avoid some inherent issues, like overfitting [9].

The evaluation of the performance of all of these machine learning models—decision trees, random forests, and neural networks—concerning disease diagnosis in a clinical setting is the objective of this study. This is done by comparing their accuracy, precision, recall, and F1 scores to determine which of these models gives out the most reliable predictions and would best support clinical decision-making.

II. METHODOLOGY

A. Data Collection and Preprocessing

The dataset in the current study is taken from, which contains different medical features with corresponding diagnostic labels. Patient demographics, clinical measurements, test results, and other important attributes are all included in this dataset to help ascertain an accurate diagnosis.

1. Data Preprocessing

Data preprocessing is one of the intrinsic elements of machine learning. It means cleaning and transforming raw data into a format ideally suited for training a model [11]. Handling missing values: The missing values refer to the values that directly impact the performance of the model. In this research, imputation using the median value for numerical features and the most frequent category for categorical features is applied for handling missing values.

Categorical Variables Encoding: Most of the machine learning algorithms require numeric inputs. In this, Label Encoding is employed in which the categorical data is converted into numeric format [12]. Numeric codes represent different diseases and demographic features of patients.

Feature Scaling: Most of the algorithms in this respect, like Neural Networks, are quite sensitive to the scale of input features. Regarding feature scaling, standardization will be done where all features will have an average of zero and a standard deviation of one [13].

2) Data Splitting

Here, the dataset will be divided into two different subsets: one for training the model and another for testing the model's performance. In the present research, a 70-30 split is used where 70% of the data is used in training the models, while 30% is kept for testing [14]. This will ensure that the models are trained with quite some data, putting another set aside to test how the performance of the models will be.

B. Implementing the Models

1) Decision Tree Classifier

Implementation of the decision tree classifier uses scikit-learn's Decision Tree Classifier [15]. This model will be trained with the preprocessed training data. This has key hyper parameters, such as the maximum depth of the tree and the minimum samples required to split an internal node that are adjusted to prevent overfitting and guarantee feasible complexity in the tree.

2) Random Forest Classifier

A Random Forest Classifier aggregates multiple Decision Trees. Again, for its implementation, one exploits sci-kit-learn's Random Forest Classifier [16]. Once more, in order to enhance performance, optimization of model hyper parameters is done via grid search. Random Forests have multiple trees whose predictions are aggregated to improve the accuracy and robustness of these predictions.

3) Neural Network Classifier

Implementation of Neural Network Classifier using sci-kit-learn's MLPClassifier. A model that is going to be trained will be a Multi-layer Perceptron with one hidden layer and a maximum of 300 iterations. It will tune, among others, the number of neurons in the hidden layer and the Activation Function. Neural networks are known to model complex relationships but require great care not to fall into overfitting.

Table-01: Hyper parameters for models

Model	**Hyper Parameters**	**Value**
Decision Tree	Max Depth	10
	Min Samples Split	5
Random Forest	Number of Trees	100
	Max Depth	None
Neural Network	Hidden Layer Size	100
	Activation Function	ReLU
	Max Iterations	300

C. Evaluation Metrics

Several evaluation metrics used to measure the performance of each model are as follows:

Accuracy: Total number of instances correctly classified out of total instances.

Precision: Ratio of true positive predictions against all positive predictions.

Recall: Ratio of true positive predictions against all actual positive instances.

F1-score: It is the harmonic mean of Precision and Recall. It provides a balanced measure of model performance [19].

Table-02: Performance Matrices

Model	Accuracy	Precision	Recall	F1-Score
Decision Tree	0.42	0.42	0.42	0.42
Random Forest	0.43	0.43	0.43	0.43
Neural Network	0.34	0.33	0.33	0.19

It is then possible to plot confusion matrices for each model's performance.

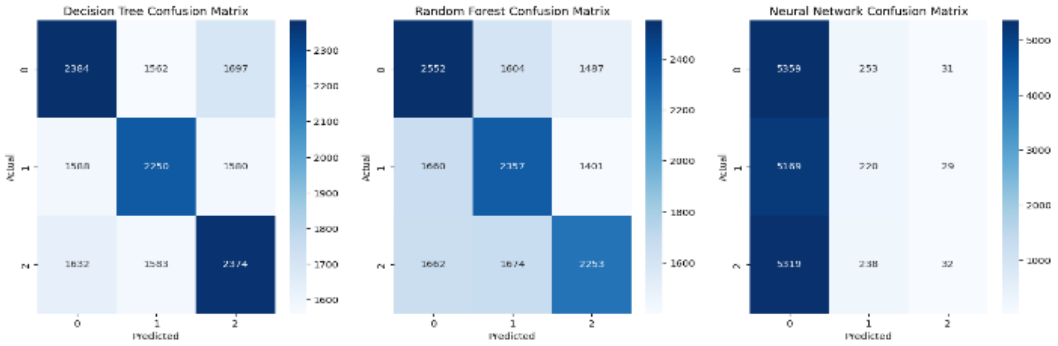

Figure-01: Confusion Matrices of all models

The counts in the case of this context will be with respect to true positive, true negative, false positive, and false negative predictions, all of which will convey insight into how well the model is doing with respect to its classification capability [20].

III. RESULT ANALYSIS

This paper reviews the different performance characteristics of DT, RF, and NN models used in disease diagnosis.

1. Decision Tree Classifier: The accuracy returned by the model for this decision tree was 42%, with uniform precision and recall of about 0.42 for each class, together with the F1-score. This means that the model predicts consistently, but sub optimally. Most likely, it suffers from overfitting in the training data. Decision trees tend to suffer from overfitting with high-dimensional data, which often results in poor performance on unseen data [1] and [2].

2. Random Forest Classifier: The random forest model did perform better than the decision tree model with an accuracy of 43%. It showed slight improvements in precision and recall for all its classes over the decision tree. Through ensemble methods—combining multiple decision trees—random forests can counter overfitting. While performance improves, the improvements are modest, which means that though RFs are more stable, further improvements must be made.

3. Neural Network Classifier: This neural network (MLPClassifier) was the least accurate, with an overall accuracy of only 34%. In particular, it had very high recall on class 0 but very low precision and recall for classes 1 and 2, which implies bias in the model to base its predictions most of the time on class 0. Neural networks are powerful and require a lot of tuning and enough data. Performance problems point out possible challenges when training and generalizing.

In summary, although random forests are much better at overall performance compared to decision trees and neural networks, all models do suffer from attaining high accuracy with balanced performance across classes. This implies that further fine-tuning and optimization of the models are necessary for their use in any disease diagnosis context.

IV. FUTURE IMPLEMENTATIONS

It has led to a line of research proposing improvements, in particular data augmentation and class balancing. While class balancing would deal with the class balance through oversampling techniques for minority classes or under sampling of majority classes, this would improve the performance of the

models. It could also be that the dataset may help if it can be augmented with synthetic samples or more diversified sources of data so that the models generalize better [7] [8].

Hyper parameter Optimization: This may be supplemented by advanced techniques for optimizing them using grid search or Bayesian optimization. This should include getting the best settings for each model, such as tuning the depth of decision trees, the number of trees in random forests, or the architecture with activation functions in neural networks.

Feature Engineering: Features can be generated or information of interest can be extracted in feature engineering. It may also benefit from an increase in the accuracy of the model. Domain knowledge can be used in designing better features to extract the subtle variations of the disease [11] and [12].

Model Ensemble Techniques: It will be outlined that, due to ensemble techniques, several models join forces for the common purpose of improving performance. This is done by different models creating a stronger one to ensure robust and more accurate predictions [13] and [14].

Deep learning methods: Even more advanced deep learning architectures, like convolutional neural networks or transformer-based models, may add a further increase in performance, mostly on large and complex datasets [15] [16].

These are some of the areas where, upon addressing them, future research would help develop the findings of this study towards more accurate and reliable machine learning models for the diagnosis of diseases, resulting in better patient outcomes and healthcare delivery.

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