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Medical Iot Devices For Chronic Disease Management

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Abstract
The forecasting of chronic illnesses is crucial within the healthcare sector. Early diagnosis of such diseases is vital. Significant advancements in technology have led to the generation of vast amounts of data in the field of computer science. The development of clinical information networks has resulted in the creation of numerous medical databases. The process of knowledge extraction and the management of extensive heterogeneous data sets has emerged as a prominent research domain, referred to as data mining. A thorough analysis of medical data facilitates the early detection of diseases, enhances patient care, and improves community services through the extensive data advancements in the biomedical and healthcare sectors. The extraction and management of knowledge from large heterogeneous data sets have become a significant area of research. Accurate health data processing aids in the early identification of diseases, patient care, and community services, driven by the growth of large data in biomedical and healthcare fields.
Keywords: *Chronic Disease, high-dimensional, community, decision-making*

1. INTRODUCTION

Many individuals with COPD experience symptoms of both types. The disease typically develops gradually over several years. Early intervention can alleviate symptoms and prevent further deterioration [1]. The primary contributors to COPD include smoking, exposure to polluted environments with high levels of dust, fumes, smoke, or gases, and second-hand smoke. Common symptoms of COPD include a persistent cough, wheezing, shortness of breath, and chest tightness [2]. It is crucial to manage this condition, as it poses significant risks to daily activities and increases the likelihood of lung cancer [9]. This is a crucial factor in assessing the actual condition of COPD, particularly from the perspective of healthcare professionals [10]. According to the review, various authors have contributed to the development of the COPD prediction model, and the discussion highlighted that the model faces challenges in accurately predicting both COPD and non-COPD cases. Research conducted by multiple authors indicates that early detection of COPD is vital to prevent progression to severe stages. The majority of studies have relied on record-based datasets, where input features are gathered through various methods, while only a few authors have focused on features derived from regions of interest in lung images, which provide significant insights for determining COPD stages [3]. The features extracted directly from lung images yield intensity values that are more precise for evaluating lung conditions, and processing these features enhances the accuracy of predictions for COPD patients. Furthermore, predictive accuracy and the area under the curve (AUC) are critical performance metrics for assessing the predictive power of machine learning models [4]. There is a need to enhance these metrics to improve the predictive capabilities of effective models [13].

2. REVIEW OF LITERATURE

In this section, we examined the feature pre-processing techniques utilized by the prior COPD prediction model. The subsequent discussion will focus on predictive methodologies and their influence on the efficacy of the prediction system, which plays a crucial role in the advancement of our system. Numerous studies have been conducted to implement effective technologies aimed at enhancing healthcare delivery through predictive modeling in healthcare systems, employing various methods [5]. In this chapter, we will explore different systems that leverage predictive modeling to enhance overall health outcomes, as well as diverse strategies for assessing the risk of chronic obstructive pulmonary disease. We will provide a summary of various predictive system methodologies, along with associated studies and findings. Sørensen and colleagues investigated the potential of utilizing texture metrics for random CT samples, where the labels are derived from external sources, and demonstrated that their proposed texture-based method achieved a classification accuracy of 69%, significantly surpassing the accuracy of voxel areas below the threshold. They explored chronic obstructive pulmonary disease through computed tomography (CT) images, extracted features, and applied the KNN method, reporting an AUC of 0.817. The authors proposed a notably superior method compared to aggregating individual region classifications into a comprehensive image classification, and in comparison to standard computerized quantitative measures in pulmonary CT. Researchers examined various multiple instance learning hypotheses in relation to COPD and revealed that while there are conceptual aspects of disease patterns associated with COPD, taking into account the overall distribution of lung tissue plaques can enhance performance, resulting in a higher AUC [6]. They proposed an unsupervised measure to assess instance stability and illustrated that a performance-stability trade-off can be achieved when evaluating multiple instance learning classifiers [11].

3. MATERIALS AND METHODS

In this learning model, labeled training data is utilized to generate predictions for previously unseen scenarios. Our prediction methods are grounded in classification techniques, specifically within the realm of machine learning. A classifier is trained on the provided dataset, allowing it to categorize data into distinct classes [12]. The classifier's role is to establish a mapping from the input (x) to the corresponding output (y), where the output variable must represent a unique value in the context of classification. Classification algorithms operate on discrete data, and the objective is to identify the decision boundary that separates the dataset into distinct classes [14]. Both binary and multiclass classification algorithms are available. Machine learning represents an intellectual endeavor that enables machines to learn and make decisions autonomously, without explicit programming [7]. We have defined specific data points or samples using predictive variables and a target variable [8]. Typically, our data is organized in a tabular format, where each row corresponds to different floral measurements across various columns, thereby facilitating the creation of a model capable of predicting the target variable. The predictive variable, also known as the independent variable, and the target variable, which may be referred to as the dependent variable or response variable, are integral to this process [15].

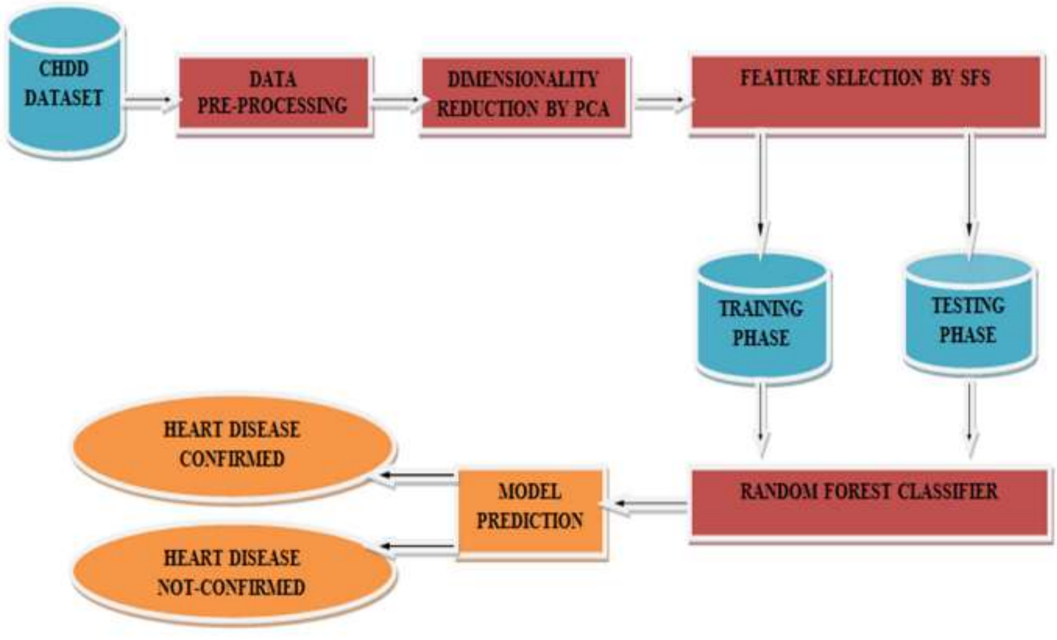

Figure 1: Proposed framework

The primary aim of supervised learning is often to either automate labor-intensive or costly manual tasks, such as medical diagnoses, or to forecast future outcomes. In supervised learning, labeled data is essential, and there are various methods to obtain it, including utilizing datasets that already contain labels.

4. RESULT AND DISCUSSION

The Multilayer Perceptron algorithm is noted for its strong predictive capabilities and employs a distinct prediction methodology. Key characteristics of the Multilayer Perceptron include: each neuron in the network features a differentiable nonlinear activation function. The network consists of one or more hidden layers, along with input and output nodes, and exhibits a high degree of connectivity.

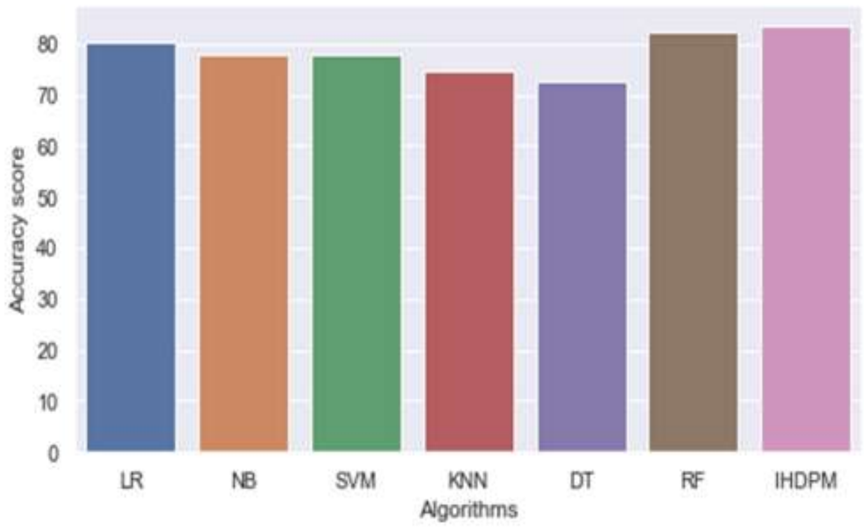

Figure 2: Accuracy plot

Training of the Multilayer Perceptron occurs in two phases: during the forward phase, the network weights are established, and input signals are propagated through the network layer by layer until the output is generated. The error signal, which is produced during the backward phase by comparing the network output to the desired response, is then propagated back through the network layer by layer.

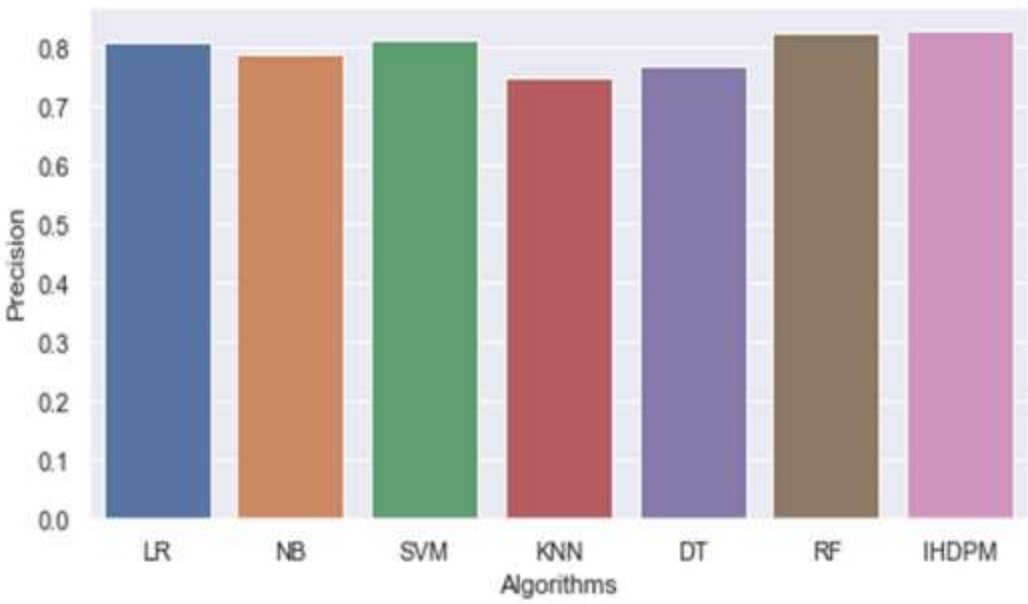

Figure 3: Precision plot

The weights and bias values are typically represented as real numbers, serving as inputs and connections. When the input values are fed into the perceptron, if the predicted output aligns with the desired output—

defined as the actual output from our training data—then the performance is deemed satisfactory, and no adjustments to the weights are necessary.

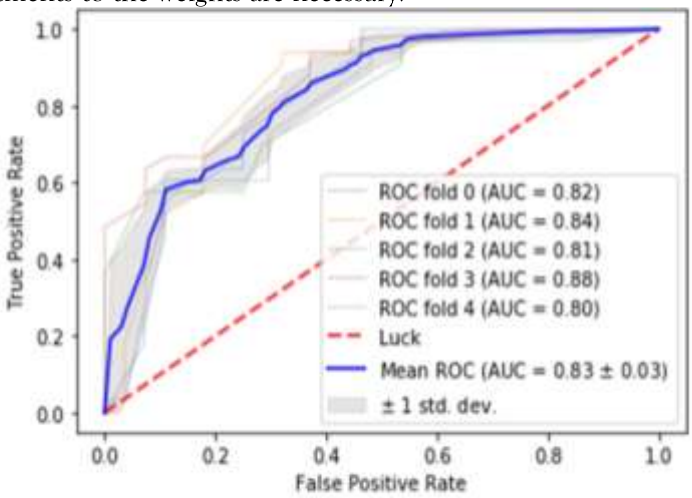

Figure 4: ROC curve

Conversely, if the predicted output diverges from the actual output or the true class of the instance, it becomes essential to modify the weights to minimize the error. This error is quantified as the difference between the predicted and actual values, and adjustments are made by calculating this discrepancy.

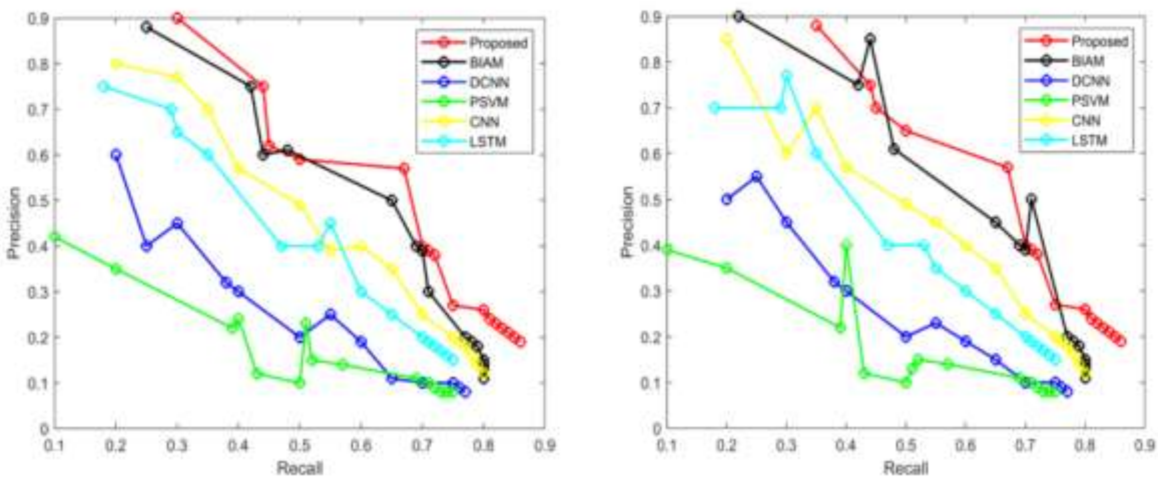

Figure 5: Precision-Recall comparison curve

Machine learning serves as a robust approach for developing predictive models, offering a range of features that can be adjusted according to the requirements of the system being developed. The predictions made by machine learning models are highly accurate, allowing for evaluation through various performance metrics

5. CONCLUSION

In the proposed model for predicting Chronic Obstructive Pulmonary Disease (COPD), we evaluated the effectiveness of a machine learning classifier utilizing the derived feature sets GSS and KDEI from the COPD dataset. Our analysis revealed that feature selection significantly influences the classifier's performance. This study employed various machine learning classifiers to predict COPD, specifically five classifiers: Stochastic Gradient Descent (SGD), Logistic Regression (LR), Multi-Layer Perceptron (MLP), Random Forest (RF), and XGBoost.

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