

CHRONIC DISEASES PREDICTION USING MACHINE LEARNING WITH DATA PREPROCESSING HANDLING: A CRITICAL REVIEW

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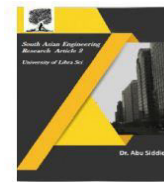
ABSTRACT

According to the World Health Organization (WHO), some chronic diseases such as diabetes mellitus, stroke, cancer, cardiac vascular, kidney failure, and hypertension are essential for early prevention. One of the prevention that can be taken is to predict chronic diseases using machine learning based on personal medical record or general checkup result. The common prediction objective is to minimize the prediction error as low as possible. The most influencing chronic diseases prediction factors are the quality of data and the choice of predictor such as machine learning methods. The five main problems those lower data quality are outliers, missing values, feature selection, normalization, and imbalance. After we ensure the quality of data, the next task is to choose the best machine learning methods. The most influencing factor to consider when we choose the predictor its performance evaluation (accuracy, recall, precision, f1-score). Thus, predicting chronic disease aims to produce increased performance and solve problems in medical data. This paper presents a Systematic Literature Review (SLR) that offers a comprehensive discussion of research on chronic diseases prediction using machine learning and its data preprocessing handling. This paper covers machine learning methods discussion such as supervised learning, ensemble learning, deep learning, and reinforcement learning. The preprocessing handling we discuss includes missing values, outliers, feature selection, normalization, and imbalance. The final discussions of this paper are open issues, and the potential future works in improving the prediction performance for chronic diseases using a data preprocessing handling and machine learning methods.

1.INTRODUCTION:

Chronic diseases, such as diabetes, cardiovascular diseases, cancer, and respiratory disorders, are among the leading causes of mortality and disability worldwide. Early detection and intervention are critical in reducing the burden of these diseases and

improving patient outcomes. Traditional diagnostic methods often rely on manual analysis and subjective decision-making, which can be time-consuming and prone to errors. In recent years, machine learning (ML) has emerged as a powerful tool for predicting chronic diseases by analyzing

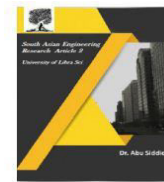


large, complex healthcare datasets. ML models can identify hidden patterns, predict risks, and assist in clinical decision-making with high accuracy. However, the effectiveness of these systems heavily depends on the quality of the input data and the preprocessing steps involved, such as handling missing values, reducing noise, and selecting relevant features. Poorly handled data can lead to inaccurate predictions and limit the applicability of ML models in real-world settings.

This review critically examines the role of data preprocessing in chronic disease prediction using machine learning. It highlights the existing challenges, evaluates current approaches, and proposes innovative solutions to enhance the reliability, interpretability, and scalability of these predictive systems. By addressing these issues, machine learning has the potential to revolutionize chronic disease management, enabling early diagnosis and personalized treatment strategies. Chronic diseases, including diabetes, heart disease, and chronic respiratory conditions, represent a significant global health burden. These diseases often develop over long periods and are influenced by a variety of risk factors such as lifestyle choices, genetics, and environmental exposures. Early prediction and intervention can substantially improve patient outcomes, reduce healthcare costs, and increase overall life expectancy. As healthcare systems worldwide seek more efficient and accurate methods for disease management, predictive modeling has emerged as a powerful tool in the early detection of chronic conditions.

Machine learning (ML) techniques, due to their ability to identify complex patterns in large datasets, have shown great promise in the prediction and diagnosis of chronic diseases. These methods can analyze vast amounts of medical data, including patient records, lifestyle factors, and diagnostic results, to predict disease outcomes with a high degree of accuracy. However, the effectiveness of machine learning models in predicting chronic diseases is heavily dependent on the quality of the data used. Raw medical data often contains missing values, inconsistencies, and noise, which can compromise the performance of ML algorithms. To address these challenges, data preprocessing plays a critical role in enhancing the quality of data before it is fed into machine learning models. Techniques such as data cleaning, normalization, feature selection, and imputation help mitigate the impact of noisy or incomplete data, ensuring that the models can learn from the most relevant and accurate information. Therefore, the success of chronic disease prediction systems hinges not only on the choice of machine learning algorithm but also on the quality of the preprocessing techniques applied to the data.

This article provides a critical review of the current state of chronic disease prediction using machine learning, with a particular focus on the role of data preprocessing in enhancing prediction accuracy. We examine the various preprocessing methods employed in the healthcare domain and discuss their impact on the performance of predictive models. Additionally, we explore the challenges associated with handling real-world healthcare data and suggest potential



ensure data quality. Hybrid and ensemble models, combined with explainable AI (XAI) frameworks, improve accuracy and interpretability for clinicians. The system is designed for real-time prediction by integrating with IoT devices and electronic health records (EHRs), while federated learning ensures data privacy and security. Additionally, it tackles class imbalance, supports continuous learning, and features a user-friendly interface for seamless clinical integration, enabling reliable and scalable chronic disease prediction across diverse populations.

Passive-Aggressive Algorithm

The Passive-Aggressive (PA) algorithm is an online learning method that adapts to new data incrementally. It is particularly effective when data arrives sequentially and is used in both classification and regression tasks. The algorithm behaves "passively" when the model's prediction is correct and makes minimal adjustments to the model, but it reacts "aggressively" when the prediction is incorrect, adjusting the model weights significantly to correct the error. The goal of the Passive-Aggressive algorithm is to minimize the hinge loss while ensuring the model is not overly influenced by outliers or errors in the data. The update rule in the PA algorithm for binary classification is:

Ensemble Learning

Ensemble Learning is a technique where multiple models (often called "weak learners") are combined to create a stronger and more accurate model. This method capitalizes on the idea that combining several

models can reduce errors, increase robustness, and improve overall accuracy. Common approaches include **Bagging** and **Boosting**. In **Bagging**, such as in **Random Forest**, several models (e.g., decision trees) are trained independently on different subsets of the training data, and their predictions are aggregated. The final prediction is typically made by majority voting for classification tasks or averaging for regression tasks:

Artificial Neural Networks (ANNs)

Artificial Neural Networks (ANNs) are computational models inspired by the human brain, consisting of interconnected layers of nodes (neurons). ANNs are powerful tools for modeling complex patterns in large-scale datasets and are widely used for tasks like classification, regression, and image recognition. In a basic neural network, data is passed through an input layer, one or more hidden layers, and an output layer. Each layer is made up of neurons, where each neuron computes a weighted sum of its inputs and passes it through an activation function.

C) Dataset

The dataset used for chronic disease prediction typically consists of various medical and demographic attributes of patients, collected from multiple sources such as hospitals, clinics, and wearable devices. This data is crucial for training machine learning models that predict the likelihood of a patient developing chronic conditions like diabetes, cardiovascular diseases, hypertension, and other long-term health issues. The dataset typically contains both structured (numerical and categorical)



and unstructured data (such as text or images), although for prediction models, the focus is primarily on structured data. Here is a detailed description of a typical Chronic Disease Prediction Dataset:

1) **Age:** The patient's age, which correlates with the likelihood of developing chronic conditions.

2) **Gender:** The patient's gender (male/female), which can influence the risk of certain diseases.

3) **Blood Pressure:** Systolic/diastolic values indicating the pressure of blood in arteries; high levels are linked to heart disease.

4) **Cholesterol:** Levels of total, LDL, and HDL cholesterol, critical for assessing cardiovascular health.

5) **Body Mass Index (BMI):** A measure of body fat based on weight and height; high BMI is a risk factor for diabetes and heart disease.

6) **Glucose Levels:** Blood glucose levels, typically fasting glucose, are key indicators for diabetes.

7) **Smoking Status:** Indicates whether the patient smokes, a major risk factor for various chronic diseases.

7) **Alcohol Consumption:** A measure of alcohol intake, which can contribute to diseases like liver cirrhosis and heart disease.

8) **Physical Activity:** A binary or categorical variable indicating the patient's level of

physical activity (sedentary, moderate, active).

9) **Dietary Habits:** Information on the patient's eating habits, which influence obesity, diabetes, and cardiovascular health.

10) **Sleep Patterns:** Data about the patient's sleep duration or quality, linked to metabolic and cardiovascular health.

11) **Electrocardiogram (ECG) Results:** Heart rhythm test results used to detect arrhythmias or heart disease.

12) **Heart Rate:** The patient's heart rate, with irregularities suggesting potential cardiovascular issues.

13) **Kidney Function Tests:** Measures of kidney health, which are important for patients with diabetes or hypertension.

14) **Disease Status:** The target variable indicating whether the patient has been diagnosed with a chronic disease (e.g., diabetes, heart disease).

15) **Risk Score:** A calculated score based on various health indicators to estimate the patient's risk of developing a chronic disease.

Patient ID	Age	Gender	Blood Pressure	Cholesterol	BMI	Glucose Level	Smoking Status	Physical Activity	Heart Disease (Target)
001	45	Male	130/85 mmHg	200 mg/dL	27.5	105 mg/dL	No	Moderate	No
002	55	Female	145/90 mmHg	250 mg/dL	30.2	160 mg/dL	Yes	Low	Yes
003	65	Male	140/88 mmHg	180 mg/dL	28.3	110 mg/dL	No	Active	No
004	50	Female	120/80 mmHg	190 mg/dL	25.4	98 mg/dL	Yes	Low	No

Fig2 .Dataset



D. Feature Selection

Feature selection is a critical step in the machine learning pipeline, especially for predictive modeling tasks like chronic disease prediction. In datasets related to healthcare, there are typically a large number of features—some of which are directly relevant to predicting diseases, while others may not provide much value. Feature selection involves identifying and retaining the most important features that contribute to the predictive power of the model. This helps in improving model accuracy, reducing complexity, and speeding up the training process.

The primary objectives of feature selection are to:

Reduce Overfitting: By eliminating irrelevant or redundant features, the model is less likely to overfit, meaning it won't memorize the training data but instead will generalize well to unseen data. Overfitting occurs when a model becomes too complex and starts to learn noise and irrelevant patterns in the data, which reduces its ability to predict future outcomes effectively.

Improve Model Performance: Reducing the number of features makes the model simpler, which often leads to faster training times and less computational overhead. A simpler model can also reduce the risk of model instability, especially when there is multi collinearity (high correlation) among features.

Enhance Interpretability: A model with fewer features is easier to interpret and understand. In healthcare, where understanding the factors that contribute to a

disease diagnosis is important, a simpler, more transparent model is highly valuable.

Types of Feature Selection Methods

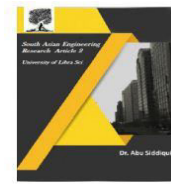
Filter Methods: Filter methods evaluate the relevance of each feature by using statistical tests or correlation measures. These methods work independently of any machine learning model and assess features based on their relationship with the target variable. Some common filter techniques include:

Correlation Coefficient: Measures the linear relationship between two variables. If a feature is highly correlated with the target variable, it is considered relevant. Features that are highly correlated with each other may be dropped to avoid multicollinearity.

III.CONCLUSION

Machine learning has immense potential to transform chronic disease prediction by leveraging large-scale healthcare data to enable early diagnosis and personalized treatment. However, the success of these systems is fundamentally tied to the quality of data preprocessing and the ability to address challenges such as imbalanced datasets, model interpretability, and privacy concerns. Existing systems, while effective in controlled research environments, often struggle with real-world applicability due to data quality issues, limited generalization, and integration challenges.

The proposed system aims to overcome these limitations by incorporating advanced preprocessing techniques, hybrid machine learning models, explainable AI frameworks, and privacy-preserving technologies like



federated learning. By enabling real-time prediction, improving model scalability, and ensuring clinical integration, this system can significantly enhance the reliability and usability of machine learning in chronic disease management.

In conclusion, continued research and innovation in data preprocessing, model development, and ethical considerations are essential to fully realize the potential of machine learning in healthcare. By addressing these areas, the proposed system can contribute to improved patient outcomes, reduced healthcare costs, and a more proactive approach to managing chronic diseases globally.

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