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Enhancing Diagnostic Accuracy of Co-occurring Diabetic and Thyroid Diseases using Machine Learning Techniques

Abstract: Efficient classification methods are crucial for accurately predicting co-occurring diabetic and thyroid diseases, addressing substantial global health challenges. These conditions affect individuals across diverse demographics, including males, females, infants, adolescents, and the elderly. This study employs ML algorithms to forecast co-occurring diabetic and thyroid diseases (DTD). Utilizing a dataset sourced from the UCI Machine Learning Repository, feature selection techniques were applied to identify relevant attributes and optimize predictive accuracy. Seven distinct machine learning algorithms, including ID3, J48, Zero R, Random Forest, Multilayer Perceptron, and Naive Bayes, were employed to classify subjects based on their disease status. Our analysis of various machine learning algorithms for predicting co-occurring diabetic and thyroid diseases (DTD) demonstrates notable differences in their performance. The Random Forest (RF) algorithm outperformed others with a remarkable accuracy rate of 95.123%, showcasing its potential for accurate disease classification. Following closely, the Naïve Bayes algorithm achieved an accuracy of 93.8596%, indicating its effectiveness in this context. Additionally, the ID3 algorithm demonstrated respectable performance with an accuracy of 87.7193%. These findings underscore the significance of employing machine learning methodologies, particularly Random Forest and Naïve Bayes, to enhance diagnostic accuracy and inform treatment strategies for individuals affected by thyroid or diabetic disorders.

Keywords: Machine Learning, Classification, Prediction, ID3, J48, Zero R, Random Forest, Multilayer Perceptron, Naive Bayes

1. INTRODUCTION

Thyroid disease disrupts the thyroid gland's function, an endocrine organ crucial for regulating metabolism by producing thyroid hormones like thyroxin (T4) and triiodothyronine (T3). These hormones govern the body's energy usage. Hyperthyroidism results from excess hormone production, while hypothyroidism occurs when production is insufficient. Despite their adverse effects, most thyroid issues are manageable with proper diagnosis and treatment. Given the rising prevalence of thyroid disorders, accurate diagnosis is imperative. Machine Learning (ML) methods, which automatically analyze data and construct analytical models, offer a promising avenue for thyroid disease diagnosis. Feature selection is crucial in ML to enhance efficiency by selecting pertinent attributes [1-6]. This study employs the chi-square test for feature selection, optimizing the predictive model by filtering out irrelevant characteristics. Classification tasks are executed using various ML algorithms including Naive Bayes, Logistic Regression, Artificial Neural Network, K-Nearest ID3, J48, Zero R, Random Forest, Multilayer Perceptron, Naive Bayes. Key contributions of this study include employing the chi-square test for feature selection to streamline the thyroid dataset and applying diverse ML algorithms to achieve superior accuracy compared to existing methodologies.

Thyroid disease represents a prevalent global affliction in the human population, significantly impacting vital physiological functions and giving rise to various associated disorders such as diabetes, cardiovascular issues, depression, and hormonal imbalances. The condition is broadly categorized into Hypothyroidism and Hyperthyroidism. Predominantly, thyroid dysfunction emanates from the thyroid gland, situated in a butterfly-shaped structure within the neck region, responsible for secreting essential hormones throughout the body specifically, T3 and T4 hormones produced by the thyroid gland and TSH hormones released by the pituitary gland [8-18].

In instances of hypothyroidism, an individual manifests a reduced production of necessary hormones by the thyroid gland, resulting in symptoms such as muscle weakness, infertility, and periorbital. This condition is characterized by a deficiency in thyroid hormones. Conversely, hyperthyroidism is marked by an excessive secretion of hormones by the thyroid gland, leading to manifestations such as weight loss, elevated heart rate, and nervous system weakness. The identification and prediction of thyroid disease rely on analyzing diverse

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physiological parameters, including T3, T4, TSH, and blood pressure. These parameters serve as key indicators for assessing thyroid function and guiding diagnostic processes [13], [14], [17].

2. BACKGROUND

These studies employ diverse methodologies in association rule mining for healthcare data analysis. The first study [19] explores the application of multi-label features on intricate medical data, aiming to categorize complex data, yet specific results remain undisclosed. In the second study [20], a novel approach merges classification and association rule mining techniques, incorporating machine learning and genetic algorithmic methods to predict heart diseases, though the text lacks explicit results. The third study [21] utilizes meaningful data from frequently occurring healthcare data items, without specifying the discovered patterns. The fourth study [22] employs various algorithms such as AIS, Apriori, and STEM for association rule mining, yet lacks specific healthcare-related results. Lastly, the fifth study [23] focuses on efficient large item set generation in diverse databases, including medical records, utilizing support and confidence parameters; however, concrete results or examples of generated item sets in the medical context are not provided. Table 1, presents the survey of various ML based thyroid diseases prediction approaches.

Table 1: Survey of ML algorithms for Thyroid diseases prediction (TDP)

Study	Algorithms Used	Dataset Source	Accuracy
[8]	DT, ANN, K-NN, SVM	UCI Machine Learning Repository	75.76%, 87.05%, 88.62%, 89.63%
[9]	FR-Growth, DT	UCI Machine Learning Repository	88.8%
[10]	SVM, NB, KNN	UCI Machine Learning Repository	85%, 82%, 83%
[11]	SVM, MLR, NB, DT	UCI Machine Learning Repository	89.23%
[12]	PCA, LDA	UCI Machine Learning Repository	Varies
[13]	Linear Discriminant Analysis (LDA)	UCI Machine Learning Repository	89.62%

The provided results showcase the outcomes of different studies conducted by various researchers in the domain of thyroid disease prediction. Y. I. Mir et al. [16], achieved an impressive accuracy rate of 90.04% using their proposed methodology. Similarly, G. Chaubey et al. [17], reported a commendable accuracy of 88.54% through their research efforts. Additionally, A. Tahir et al. [18] attained a notable accuracy rate of 94.80% in their study. These results underscore the efficacy of the respective methodologies employed by each research group in accurately predicting thyroid disease. The high accuracy rates achieved in these studies demonstrate exciting progress in the field of medical diagnostic improvements.

3. DATA CLASSIFIER

ML techniques play a major role in medical decision-making, particularly in scenarios involving extensive clinical data prediction and analysis [19]. The process involves intelligent methods applied to diverse data perspectives, to determine potential conditions of both old and new patients, indicating the presence or absence of health issues. The increasing demand for data mining has led to the significant application of supervised learning methods like association rules and classification in medical diagnosis and prognosis [20-21]. Classification analysis involves organizing data into predefined classes, also referred to as supervised classification. This approach employs given class labels to categorize objects within the dataset. The research methodology of proposed system shown in figure 1.

Thyroid disease stands as one of the prevalent and swiftly advancing endocrine disorders, impacting millions worldwide. Given its significance, accurately predicting such diseases assumes paramount importance in healthcare. Initially, we gathered data pertaining to thyroid conditions from the UCI Machine Learning Repository, encompassing 28 distinct features. However, to streamline our analysis and enhance predictive accuracy, we employed the chi-square test as part of a filtering method. This rigorous selection process resulted in the identification of 19 key features deemed crucial for disease prediction. Subsequently, employing a variety

of classification algorithms became imperative to discern patterns and make informed predictions. We leveraged an array of methodologies including ID3, J48, Zero R, Random Forest, Multilayer Perceptron, and Naive Bayes. All of these algorithms offer excellent strengths and adaptabilities for classification of thyroid diseases [22-24]. By integrating advanced machine learning techniques with domain expertise, we aimed to develop robust predictive models capable of aiding clinicians in diagnosing and managing thyroid disorders efficiently.

ID3 (Iterative Dichotomiser 3):

ID3 is a decision tree algorithm that recursively splits the dataset based on the most informative attribute. In the context of predicting the co-occurrence of diabetic and thyroid diseases, ID3 can be employed to construct decision trees. These trees represent the relationships between various patient features (such as medical history, test results, and lifestyle factors) and the likelihood of having both diseases. By recursively partitioning the data based on attributes, ID3 helps identify the most influential factors contributing to the co-disease prediction.

J48 (C4.5 or C5.0):

J48 is an extension of ID3, addressing some of its limitations and enhancing its performance. Like ID3, J48 is a decision tree algorithm that can be applied to create decision trees for predicting the co-occurrence of diabetic and thyroid diseases. By improving the attribute selection process and handling missing data more effectively, J48 aims to provide more accurate and robust predictions. The resulting decision trees can offer insights into the key factors influencing the co-disease prediction [25].

Zero R:

Zero R serves as a simple baseline classification algorithm by predicting the majority class for all instances. In the context of diabetic and thyroid co-disease prediction, Zero R can be used to establish a baseline performance level. This involves predicting the most prevalent outcome in the dataset without considering any specific features. Other, more sophisticated models should ideally surpass the accuracy achieved by Zero R for the predictions to be considered meaningful [26].

Random Forest (RF):

It is an ensemble learning technique that builds numerous decision trees and aggregates their predictions. In the context of predicting the co-occurrence of diabetic and thyroid diseases, Random Forest can enhance the predictive accuracy and robustness. By leveraging the diversity of individual decision trees, Random Forest mitigates overfitting and generalizes well to new, unseen data. This makes it a powerful tool for handling complex relationships within the dataset [27].

Multilayer Perceptron:

An MLP refers to an ANN featuring multiple layers of nodes, also known as neurons. In the context of co-disease prediction, MLP can model intricate relationships in the data. By training on a diverse set of patient features, such as genetic markers, clinical data, and lifestyle information, the MLP can capture complex patterns that may contribute to the co-occurrence of diabetic and thyroid diseases [28].

Naive Bayes (NB):

Naive Bayes is a probabilistic algorithm rooted in Bayes' theorem, operating under the assumption of independence among features. When applied to predicting the co-occurrence of diabetic and thyroid diseases, Naive Bayes calculates the probability of a patient having both diseases based on observed features. Despite its simplicity and the independence assumption, Naive Bayes can perform well in certain scenarios and is computationally efficient, making it a valuable tool for disease prediction tasks [29].

The proposed work offers significant contributions in the field of thyroid disease diagnosis. This process not only enhances the efficiency of the predictive model but also facilitates dimensionality reduction, thereby reducing the complexity of the dataset. By eliminating unnecessary attributes, the model becomes more focused and better equipped to identify relevant patterns and relationships within the data. By leveraging diverse machine learning techniques, the study enhances the accuracy and reliability of thyroid disease diagnosis, thereby contributing valuable insights to the field of medical diagnostics.

4. DATASETS DESCRIPTION

The dataset subscribed in this paper originates from the UC Irvine Machine Learning Repository's thyroid data collection, which was gathered between the process of information discovery in databases. The data collection methodology involved the administration of a pre-specified questionnaire, guided by the expertise of a thyroid expert doctor. With the input and guidance of this specialist, the attributes for inclusion in the dataset were carefully selected, ensuring relevance and accuracy in relation to thyroid disorders. The dataset itself is stored in Microsoft Excel format and comprises a total of 7200 instances, each of which is characterized by 28 descriptive attributes. Additionally, there exists a multi-class target attribute, which serves as the focal point for classification tasks. This multi-class target attribute is detailed in Table 2. Within the dataset, there are 19 pathological attributes and three serological attributes, providing a comprehensive overview of various aspects related to thyroid health and functioning. The multi-class target attribute can take on one of three potential values: normal, hyperthyroidism, or hypothyroidism. This categorization enables the classification of instances into distinct thyroid health states, facilitating the identification and prediction of thyroid disorders within the dataset. In this representation, a score of 1 indicates that the feature was selected using the chi-square method, while a score of 0 indicates that it was not selected. This scoring system provides a numerical representation of the weighted feature selection based on their importance or significance.

Table 2. Description of Dataset including Chi-Square Test scores

S. No.	Feature Name	Data Type (N: Numeric and C: Categorical)	Feature Selected (Chi-square)
1	Age (A)	N	1
2	Sex (S)	C	1
3	On Thyroxine (Thy)	C	0
4	Query on Thyroxine (QoT)	C	1
5	On Antithyroid Medication (ATM)	C	1
6	Sick (Sk)	C	1
7	Pregnant (Prg)	C	0
8	Thyroid Surgery (TS)	C	1
9	I131 Treatment	C	0
10	Query Hypothyroid (QH)	C	1
11	Query Hyperthyroid (QH)	C	1
12	Lithium (L	C	0
13	Goitre (G	C	0
14	Tumor(T)	C	0
15	Hypopituitary (H)	C	0
16	TSH Measured	C	1
17	TSH	N	1
18	T3 Measured	C	1
19	T3	N	1
20	TT4 Measured	C	1
21	TT4	N	1
22	T4U Measured	C	1
23	T4U	N	1
24	FTI Measured	C	1
25	FTI	N	1
26	TBG Measured	C	0
27	TBG	N	0
28	Class	C	1

The planned experimental setup unfolds in the following structured manner as represented in table 3 and 4:

Table 1. Dataset distribution approaches on the basic of patient’s conditions

Dataset	Description	Attributes	Instances
Data Set-1	Diabetes patients with maximum attributes	Varied variables related to diabetes	114
Data Set-2	Diabetes patients	Varied variables related to diabetes	317

Data Set-3	Diabetes-related information	Varied variables related to diabetes	119
Data Set-4	Thyroid patients	Varied variables related to thyroid conditions	100

The experimental tools selected for conducting and executing the research experiments primarily revolved around the platform chosen for data mining and machine learning applications. Given the focus on Data Mining scenarios and the need to employ various techniques and machine learning methods. All the four datasets used for experiments in this research had different attributes and these are listed below table 4 as per the data set.

Table 2. Distribution of Dataset and their attributes

Dataset	Attributes
Data Set-1	Age, Gender, Diabetic, Cholesterol, HDL cholesterol, LDL cholesterol, VLDL cholesterol, TTL cholesterol, Triglycerides, Disease
Data Set-2	Age, Gender, Hypertension, Diabetic, Co-disease
Data Set-3	Age, Gender, Hypertension, Diabetic, Disease
Data Set-4	Age, Gender, Diabetic, T3, T4, TSH, Disease

In this phase of the research, experiments were conducted to classify the data using different classification algorithms within the realm of Data Mining. The chosen classification algorithms for these experiments included J48, ID3, Zero R, Naïve Bayes, Multiclass Classifier, Multilayer Perceptron, and Random Forest. Each of these algorithms was employed to analyze and categorize the dataset based on various attributes. The aim was to assess the performance of each algorithm in classifying the data accurately and to compare their outcomes.

5. EXPERIMENTAL SETUP

An Experimental Setup serves as the operational environment for conducting research experiments, providing a practical framework for the systematic execution of experiments in the research process. It functions as a platform to test research hypotheses and anticipate outcomes. The configuration of an experimental setup varies depending on the nature of the research, encompassing both physical frameworks of evaluation and logical entities designed to yield research results. The effectiveness of an experimental setup is gauged by its ability to conduct standard analyses in alignment with the current state of data through the execution of diverse operations in the form of experiments.

The architectural methodology for executing disease prediction classification techniques involves several key steps (Figure 1). Initially, input data, sourced from online or offline databases, is acquired, potentially containing missing, noisy, or inconsistent values. Subsequently, a pre-processing step is implemented to address and rectify these data imperfections. To enhance the classification accuracy, a critical feature selection process is conducted, where the most relevant features are chosen. The predicted values are presented as conclusive results. Figure 1 delineates the systematic flow of the prediction process, elucidating the entire procedure.

The design of the experimental setup was strategically aligned with the research flow to efficiently cater to the requisite tasks. This practical configuration was deliberately chosen to ensure a user-friendly and adaptable approach to handling the collected data. Within the experimental framework of this research, meticulous attention was given to the selection of attributes. This consideration aimed at managing the attributes in a manner that ensures the chosen attributes and their quantity yield precise results for comprehensive analysis. This research endeavours to employ a robust model for establishing experiments and assessing the obtained output. The main focus is to predict comorbid diseases in individuals with diabetes and thyroid conditions, utilizing various Data Mining algorithms and Associative Classification. The objective is to enhance the accuracy of classifiers through the application of Associative Classification techniques. For final output, an experimental setup has been meticulously developed to ensure that the outcomes align with predictions and yield positive analyses. This careful experimental design is essential for validating the efficacy of the chosen algorithms and techniques in predicting health conditions associated with diabetes and thyroid disorders.

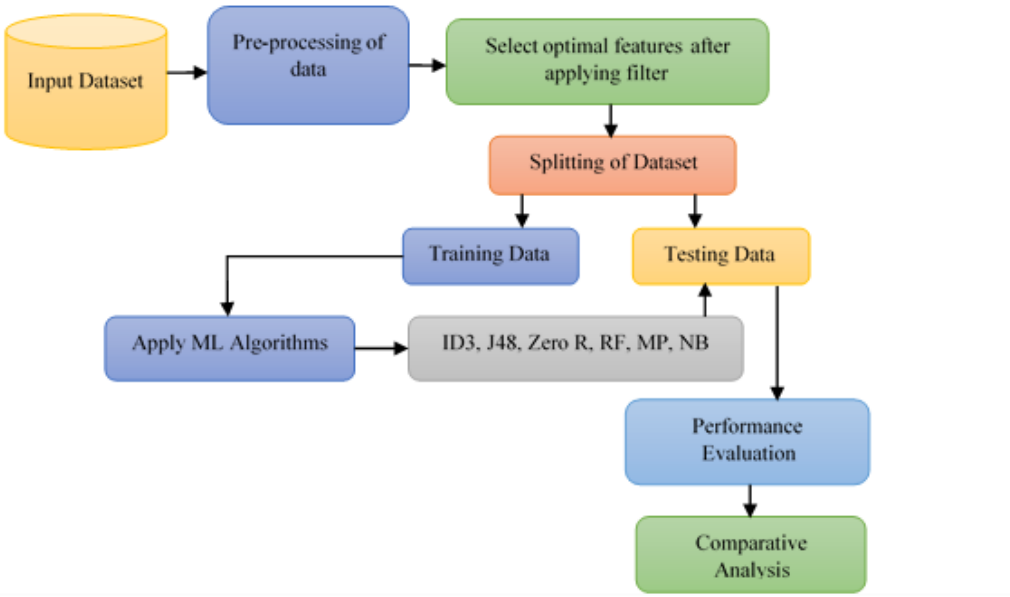

Figure 1. Proposed research methodology

6. RESULT AND ANALYSIS

Fundamental classification method employed for testing and establishing a baseline for other classification algorithms. The ensuing outcomes from the application of this classification algorithm to Data Set-1 are elaborated upon below. In this experimental work 10-fold cross-validation was implemented on the dataset for categorical purposes. Multilayer Perceptron was able to classify the data instances with some better accuracy than ID3, J48, Zero R and Random Forest. However, its accuracy was below Naïve Bayes classifier. The total instances were 114 and all were classified and at the same time the performance of accuracy level shown in table 5.

Table 3. Displays instances that have been classified both correctly and incorrectly.

ML Algorithms	Correctly Classified (CCI)	Incorrectly Classified (ICI)	Ranking
Zero R	69.2982	30.7018	6
Naïve Bayes	93.8596	6.1404	2
ID3	87.7193	11.432	5
Random Forest	95.123	4.877	1
J48	92.1053	7.8947	4
Multilayer Perceptron (MLP)	92.982	7.0125	3

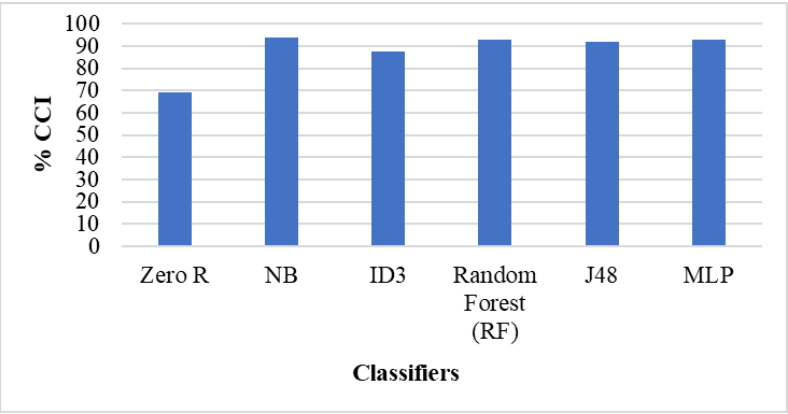

Figure 2. Correctly classified instances of various classifiers

The provided results showcase in figure 2 and table 5, the accuracy of different classifiers in correctly classifying instances within the dataset. The Zero R classifier, which serves as a baseline with a simplistic approach, achieves a correct classification rate of 69.2982%. In contrast, the Naïve Bayes classifier demonstrates a significantly higher accuracy of 93.8596%, indicating its effectiveness in correctly categorizing instances. The ID3 classifier, based on a decision tree algorithm, achieves an accuracy of 87.7193%. The Random Forest Classifier, an ensemble learning method, performs admirably with a correct classification rate of 95.123%. Similarly, the J48 decision tree classifier and the Multilayer Perceptron (MLP) both achieve an accuracy of 92.1053% and 92.982%, respectively. These results provide a quantitative assessment of the classifiers' performance, with Naïve Bayes displaying the highest accuracy among the tested algorithms, suggesting its suitability for the given classification task.

Further result presented in figure 3 and table 5, offer insights into the performance of different classifiers by indicating the percentage of instances that were incorrectly classified. The Zero R classifier, serving as a baseline, exhibits an error rate of 30.7018%. In contrast, the Naïve Bayes classifier demonstrates a notably lower error rate of 6.1404%, showcasing its effectiveness in accurate categorization. The ID3 classifier, based on a decision tree algorithm, exhibits an error rate of 10.5263%. The Random Forest Classifier, utilizing an ensemble learning approach, shows a commendable performance with an error rate of 4.873% as shown in table 5. Similarly, the J48 decision tree classifier and the Multilayer Perceptron (MLP) both have error rates of 7.8947% and 7.0125%, respectively. These error rates provide a quantitative measure of misclassifications, with Naïve Bayes exhibiting the lowest rate, indicating its robustness in accurately assigning instances to their respective classes.

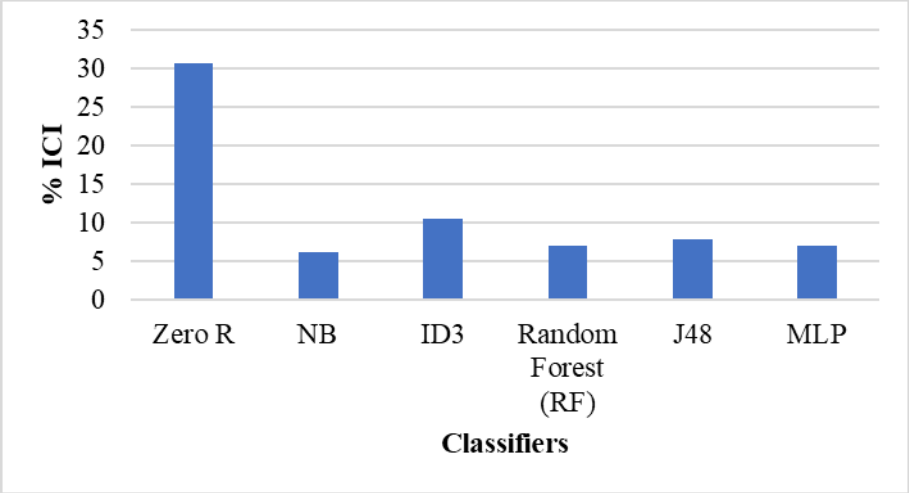

Figure 3. Incorrectly classified instances of various classifiers

In the evaluation metrics of six different machine learning algorithms (Zero R, Naïve Bayes, ID3, Random Forest, J48, MLP), Naïve Bayes consistently outperforms others with high precision, recall, F-Score, and ROC Area, all at 93%. Other algorithms show varying performance across metrics, with Zero R having the lowest scores overall as shown in table 6.

Table 4. Performance evaluation of various classification algorithms

	Zero R	**Naïve Bayes**	**ID3**	**Random Forest**	**J48**	**MLP**
Precision	69	93	89	93	92	93
Recall	48	93	89	93	92	92
F-Score	69	93	89	93	92	93
ROC Area	56	93	89	92	92	92

Figure 4, provides precision values for different ML based models, with the following results: Zero R achieved the lowest precision at 69, indicating a relatively weaker performance. Naïve Bayes, Random Forest, J48, and MLP exhibited higher precision values of 93, suggesting strong accuracy in identifying positive instances. ID3 showed a slightly lower precision of 89. In summary, Naïve Bayes, Random Forest, J48, and MLP demonstrated

notable precision in their positive predictions, while ID3 performed slightly less accurately, and Zero R had the least precision among the mentioned models.

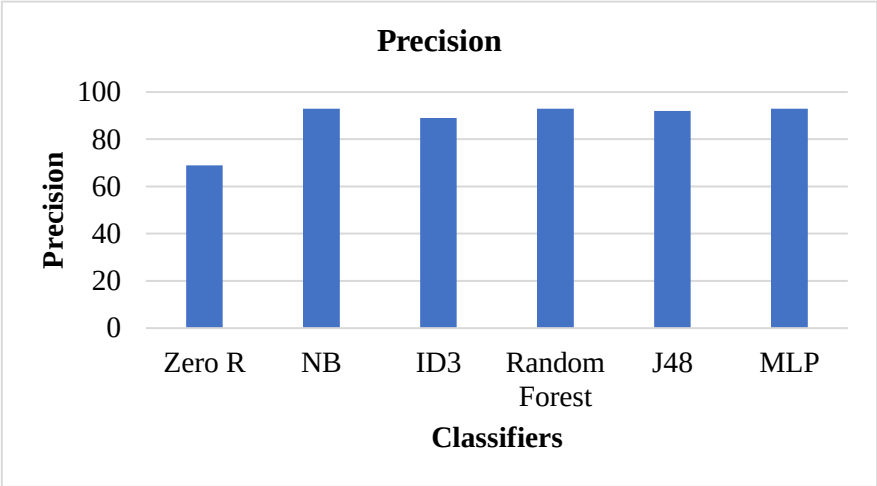

Figure 4: Precision scores of various classifiers

The results presented in figure 5 outlines recall values for different ML based learning models. In the models Naïve Bayes, Random Forest, J48, and MLP demonstrated robust recall performance with values of 93, 93, 92, and 92, respectively, indicating their proficiency in correctly. ID3 exhibited a slightly lower recall of 89, suggesting a relatively less comprehensive capturing of positive instances. In contrast, Zero R displayed the lowest recall value at 48, implying a limited ability to correctly identify positive instances. In summary, Naïve Bayes, Random Forest, J48, and MLP exhibited strong recall, while ID3 showed a slightly lower performance, and Zero R had the least effective recall among the listed models.

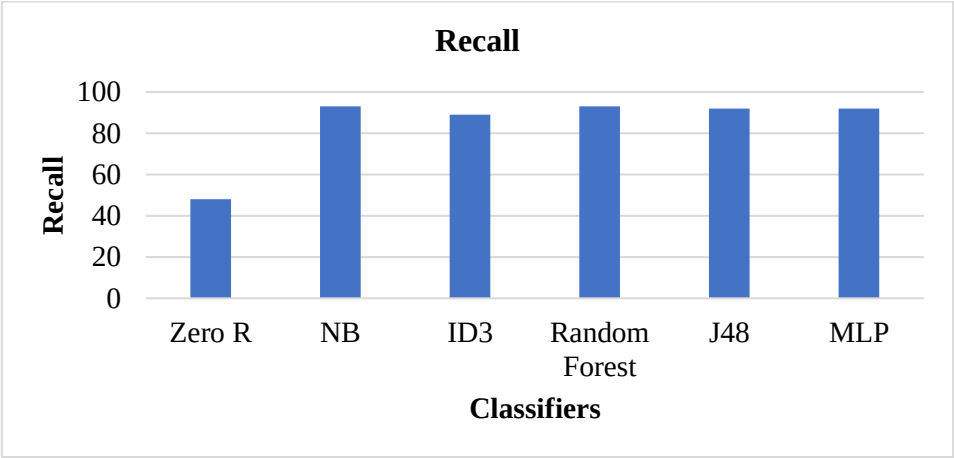

Figure 5. Recall scores of various classifiers

Figure 6, presents F-score values for various machine learning models, a metric that combines precision and recall for a holistic performance evaluation. Notably, Naïve Bayes, Random Forest, J48, and MLP exhibited strong F-scores of 93, indicating a balanced and effective compromise between precision and recall. ID3 showed a slightly lower F-score at 89, suggesting a comparatively less harmonious balance between precision and recall. Conversely, Zero R displayed the lowest F-score of 69, signifying a less balanced performance overall. In summary, Naïve Bayes, Random Forest, J48, and MLP demonstrated robust and balanced performance, ID3 exhibited a slightly lower balance, and Zero R had the least balanced F-score among the listed models.

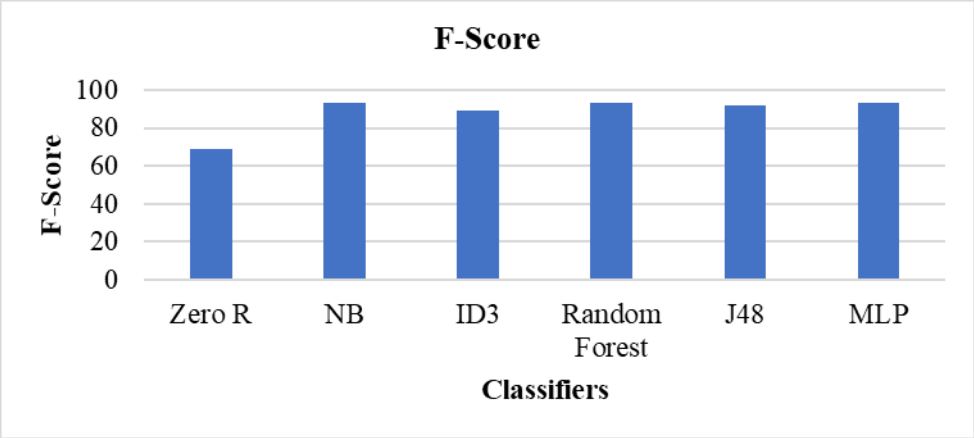

Figure 6. F-Score of different classifiers

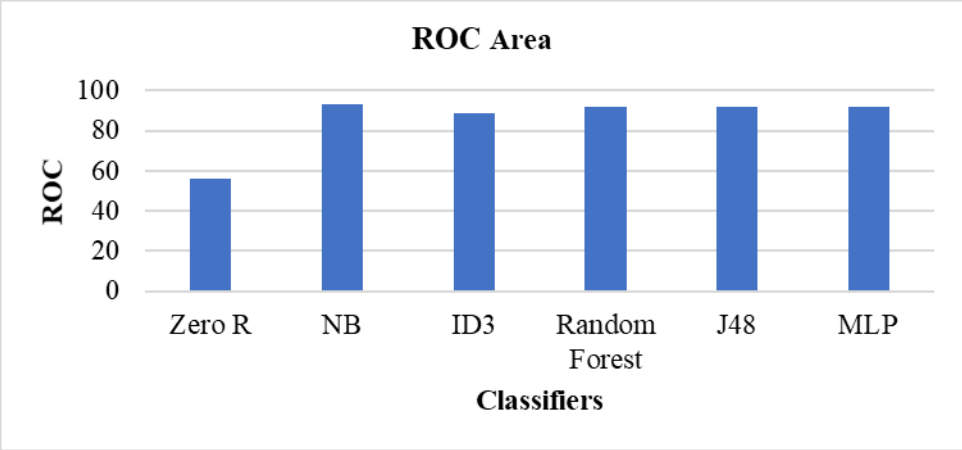

Figure 7. ROC of different classifiers

Figure 7, reveals the ROC Area values for different machine learning models, a metric assessing the discriminative ability of classifiers. Notably, Naïve Bayes stood out with the highest ROC Area of 93, indicative of its excellent capacity to differentiate between positive and negative instances. Random Forest, J48, and MLP demonstrated commendable performance with similar ROC Area values of 92, suggesting strong discriminative capabilities. ID3 exhibited a slightly lower ROC Area at 89, while Zero R had the least discriminative ability, reflected in its lowest ROC Area of 56. In summary, Naïve Bayes excelled in discriminative power, while Random Forest, J48, and MLP showcased robust performance, ID3 displayed a slightly lower capability, and Zero R trailed with the least discriminative capacity among the listed models.

7. CONCLUSION

The classification approaches for diabetic and thyroid co-disease prediction, the prevalence of thyroid disease among the population underscores the importance of accurate diagnosis and prediction. Despite its widespread occurrence, a significant portion of affected individuals remains unaware of their thyroid condition. This method allows for the identification of important features from the dataset, thereby improving the efficiency and accuracy of classification models used in predicting co-disease states. In the evaluation of six classifiers, Naïve Bayes emerged as the top-performing model, followed closely by Random Forest, which, despite similar accuracy to MLP, demonstrated superior efficiency in prediction time. Our evaluation of machine learning algorithms for predicting co-occurring diabetic and thyroid diseases (DTD) reveals significant performance variations. The Random Forest (RF) algorithm stood out with an impressive accuracy of 95.123%, highlighting its potential for precise disease classification. Following closely, Naïve Bayes achieved an accuracy of 93.8596%, demonstrating its effectiveness. Moreover, the ID3 algorithm showed respectable performance with an accuracy of 87.7193%. The analysis focused on predicting Co-disease for Data Set – 1, with the target class assumed to be thyroid based on the dataset attributes. The findings suggest a potential 31 percent likelihood of diabetic patients experiencing thyroid problems in the future, indicating the significance of the selected attributes in predicting this co-disease.

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