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Comparative Analysis of Kidney Disease Detection Using Machine Learning

Mohammad Diqi, I Wayan Ordiyasa, Marselina Endah Hiswati

***Abstract*— This research aimed to compare the performance of ten machine learning algorithms for detecting kidney disease, utilizing data from the UCI Machine Learning Repository. The algorithms tested included K-Nearest Neighbour, RBF SVM, Linear SVM, Neural Net, Decision Tree, Naïve Bayes, AdaBoost, Random Forest, Gaussian Process, and QDA. The evaluation metrics used were accuracy, precision, recall, and F1-score. The findings revealed that AdaBoost was the most effective algorithm for all evaluation metrics, achieving an accuracy, precision, recall, and F1-score of 1.00. Random Forest and RBF followed closely, while Naïve Bayes and QDA had the lowest performance. These results suggest that machine learning algorithms, especially ensemble methods such as AdaBoost, can significantly improve the accuracy and efficiency of detecting kidney disease. This can lead to better patient outcomes and reduced healthcare costs.**

***Index Terms*—kidney disease, machine learning, algorithm comparison, medical diagnosis, evaluation metrics.**

I. INTRODUCTION

A substantial proportion of the world's population suffers from kidney disease. Kidney disease (CKD) is highly prevalent in Iran, affecting around 15.14% of the population, as reported by Bouya et al. [1]. Eckardt et al. [2] found that the incidence of CKD is higher than 10% and can exceed 50% in high-risk populations. Coresh et al. [3] estimated the incidence of CKD in the United States to be 13.1% between 1999 and 2004, indicating that the overall prevalence of kidney disease is at least 10% and is likely higher in high-risk populations.

Research suggests that machine learning algorithms can enhance the speed and accuracy of diagnosing kidney disease. S et al. [4] found that machine learning models are more practical when predicting CKD from key physiological parameters. Qin et al. [5] demonstrated that random forest achieved the highest performance, with a diagnostic accuracy of 99.75%. Wang [6] discovered that the BP neural network outperforms logistic regression when diagnosing kidney disease.

Each of the many machine learning algorithms available for diagnosing kidney disease has its benefits and drawbacks. David et al. [7] found that the IBK and random tree classification methods had the highest accuracy of 93.6585% for predicting diabetic kidney disease. Naive Bayes obtained the highest accuracy possible for a smaller dataset of 23 attributes for kidney disease, as discovered by Khan et al. [8]. Chowdhury et al. [9] determined the best accuracy, sensitivity, and specificity to be 0.96 (±0.01), 0.98 (±0.01), and 0.93 (±0.02), respectively. According to Roy et al. [10], the extra trees classifier model provided the highest accuracy of 99.36% with one of the quickest execution periods.

The effectiveness and scalability of machine learning solutions are influenced by the sample and preprocessing methods chosen. Alshdaifat et al. [11] found a statistically significant difference in the effects of preprocessing methods when comparing the effectiveness of different classification algorithms. Chandrasekaran et al. [12] demonstrated that even significantly smaller datasets could provide as much information as the original dataset. Huang et al. [13] discovered that data preprocessing approaches could have positive and negative effects on the prediction performance of ML methods.

While machine learning algorithms can potentially identify kidney disease, biases, and ethical concerns must be addressed before they can be used in medical diagnosis. Ganz et al. [14] reported that research into fair algorithms and mitigating bias in data and algorithms had increased recently. Gianfrancesco et al. [15] found potential sources of bias in machine learning algorithms, such as missing data and unidentified patients, small sample size and underestimation, misclassification, and measurement error, among others.

Several interventions have been shown to improve kidney disease detection and treatment in real-world settings, including point-of-care CKD screening and multifactorial interventions, as reported by [16]–[18].

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Mohammad Diqi is with the Informatics Department of Saint and Technology Universitas Respati Yogyakarta, Indonesia (email diqi@respati.ac.id)

I Wayan Ordiyasa is with Informatics Department of Saint and Technology Universitas Respati Yogyakarta, Indonesia (email wayan@respati.ac.id)

Marselina Endah Hiswati is Informatics Department of Saint and Technology Universitas Respati Yogyakarta, Indonesia (email marsel.endah@respati.ac.id).

However, limitations in statistical methods and problems with data reporting have been highlighted as potential sources of bias or error in research on the detection of kidney disease [19]–[22].

Overall, these studies indicate that machine learning algorithms can play a significant role in the accurate and efficient detection of kidney disease. However, the choice of algorithm, dataset, preprocessing techniques, and evaluation metrics must be carefully considered to ensure the results' accuracy and generalizability. Ethical concerns, potential biases, and other sources of error must also be addressed to ensure the appropriate and efficient application of machine learning algorithms in medical diagnosis.

This research aims to evaluate the effectiveness of different machine learning methods for detecting kidney disease using data from the UCI Machine Learning Repository. K-Nearest Neighbor (KNN), RBF SVM, Linear SVM, Neural Net, Decision Tree, Naive Bayes, AdaBoost, Random Forest, Gaussian Process, and QDA are among the methods being tested. To determine which algorithm is the most effective at identifying kidney disease, we will compare its accuracy, precision, recall, and F1-score with those of the other algorithms.

This research is significant because early diagnosis of kidney disease is essential for better patient outcomes and lower healthcare expenses. Although the performance of various machine learning algorithms can vary significantly depending on variables like dataset and preprocessing techniques, they can potentially improve the accuracy and efficiency of detecting kidney disease. This research can shed light on the best algorithms and methods for detecting kidney disease by comparing the performance of different machine learning algorithms. It can contribute to developing more efficient and accurate methods for diagnosing kidney disease, ultimately improving patient outcomes and reducing healthcare costs.

II. METHODS

A. Dataset

The research team obtained the dataset from the UCI Machine Learning Repository for this study. This dataset comprises 400 patient records and aims to predict the presence of kidney disease based on specific diagnostic measurements included in the dataset. It is crucial to note that all data collection procedures were carried out in strict adherence to the ethical guidelines and terms of use of the UCI Machine Learning Repository.

B. Data Preprocessing

We conducted various preprocessing steps to prepare the dataset for analysis with machine learning algorithms [23]. Firstly, we eliminated any missing values in the dataset. We also performed feature scaling to normalize the values of different features, ensuring that they were in the same range for consistency. In addition, we used one-hot encoding to convert categorical data into numerical data, facilitating their inclusion in the analysis. Finally, we split the dataset into two sets for training and testing purposes. Specifically, 80% of the data was used for training, while the remaining 20% was allocated for testing.

C. Machine Learning Algorithms

We compared ten distinct machine learning methods for identifying kidney disease [24]–[26], namely K-Nearest Neighbor (KNN), RBF SVM, Linear SVM, Neural Net, Decision Tree, Naïve Bayes, AdaBoost, Random Forest, Gaussian Process, and QDA. The implementation of these algorithms was done using the Scikit-Learn library in Python.

D. Model Evaluation

In this study, we evaluated the performance of ten different machine learning algorithms for detecting kidney disease using the following evaluation metrics. **Accuracy** measures the proportion of correctly predicted instances out of the total number of instances [27]. **Precision**, which quantifies the accuracy of positive predictions relative to the total number of positive predictions [28]. **Recall** quantifies how often a positive outcome is accurately predicted close to the total number of positive outcomes [29]. **F1-score**, which is a harmonic mean of precision and recall that provides a balance between them [29].

III. RESULTS

A. Accuracy

The study results indicate that machine learning algorithms can effectively detect kidney disease. AdaBoost had the highest performance among the ten algorithms tested, achieving perfect accuracy, precision, recall, and F1-score, as shown in Table 1. Random Forest and RBF SVM had the second-highest performance for all metrics, while Naïve Bayes and QDA had the lowest performance. These findings suggest that ensemble methods like AdaBoost and other methods such as Random Forest and RBF SVM are powerful tools for detecting kidney disease, potentially leading to improved patient outcomes and reduced healthcare costs.

Table 1. Accuracy of Algorithms

Algorithms	Accuracy
KNN	0.9750
Linear SVM	0.9500
RBF SVM	0.9875
Gaussian	0.9750
Decision Tree	0.9375
Random Forest	0.9875
Neural Net	0.9750
AdaBoost	**1.0000**
Naïve Bayes	0.9000
QDA	0.7500

B. Confusion Matrix

Based on TP, FN, FP, and TN results, we can see that most algorithms have high TP rates, indicating an excellent ability to detect positive cases of kidney disease accurately. AdaBoost achieved the highest TP rate with 33 correct positive predictions and 0 false negative predictions, as shown in Table 2. This suggests

that AdaBoost is the most effective algorithm for detecting positive cases of kidney disease in this dataset.

Table 2. Confusion Matrix

Algorithms	TP	FN	FP	TN
KNN	32	1	1	46
Linear SVM	33	0	4	43
RBF SVM	33	0	1	46
Gaussian	32	1	1	46
Decision Tree	32	1	4	46
Random Forest	32	1	0	47
Neural Net	32	1	1	46
AdaBoost	**33**	**0**	**0**	**47**
Naïve Bayes	33	0	8	39
QDA	18	15	5	42

On the other hand, we can see that Naïve Bayes had the highest number of false positive predictions (8) and the lowest TP rate (33). This indicates that Naïve Bayes may not be a reliable algorithm for detecting kidney disease in this dataset.

Regarding FN rates, QDA had the highest number of false negative predictions (15), which means that it may not be very effective in detecting true positive cases of kidney disease.

Overall, it is essential to consider both TP and FP rates when evaluating the performance of these algorithms. AdaBoost seems to have achieved the best balance between TP and FP rates, with a high TP rate and a low FP rate.

C. *Classification Report*

Based on the results of the classification report, it can be seen that AdaBoost had the highest performance among all the algorithms, achieving perfect scores for all three metrics, as seen in Table 3.

Table 3. Classification Report

Algorithms	Precision	Recall	F1-score
KNN	0.97/0.98	0.97/0.98	0.97/0.98
Linear SVM	0.89/1.00	1.00/0.91	0.94/0.96
RBF SVM	0.97/1.00	1.00/0.98	0.99/0.99
Gaussian	0.97/0.98	0.97/0.98	0.97/0.98
Decision Tree	0.89/0.98	0.97/0.91	0.93/0.95
Random Forest	1.00/0.98	0.97/1.00	0.98/0.99
Neural Net	0.97/0.98	0.97/0.98	0.97/0.98
AdaBoost	**1.00/1.00**	**1.00/1.00**	**1.00/1.00**
Naïve Bayes	0.80/1.00	1.00/0.83	0.89/0.91
QDA	0.78/0.74	0.55/0.89	0.64/0.81

Random Forest, RBF SVM, KNN, and Gaussian Process also performed well, with high scores for precision, recall, and F1-score. On the other hand, Naïve Bayes and QDA had the lowest performance for all three metrics, with lower precision, recall, and F1-score values. It is worth noting that QDA had particularly low recall scores, indicating many false negatives. Overall, the results suggest that AdaBoost is the most effective algorithm for accurately detecting kidney disease in this dataset, with Random Forest and RBF SVM as strong alternatives.

IV. DISCUSSION

A. *Performance Comparison*

The results indicate that AdaBoost outperformed all other algorithms, achieving perfect accuracy, precision, recall, and F1-score. Random Forest and RBF SVM also performed well, with high accuracy and F1-score values. On the other hand, Naïve Bayes and QDA had the lowest performance for all evaluation metrics, indicating that they may not be suitable for detecting kidney disease.

It is worth noting that the results obtained from the evaluation metrics of precision, recall, and F1-score are more informative than accuracy alone. For example, while the KNN and Gaussian Process accuracy are the same, their precision, recall, and F1-score values differ slightly. This means that precision, recall, and F1-score can provide a more detailed understanding of the strengths and weaknesses of each algorithm.

The results show that machine learning algorithms can effectively detect kidney disease based on diagnostic measurements. The high accuracy and F1-score values achieved by several algorithms suggest that they could aid medical professionals in making accurate and timely diagnoses. However, further research is necessary to validate the performance of these algorithms in clinical settings and to identify any potential limitations or biases.

B. *Interesting Patterns and Observations*

Several exciting patterns and observations can be noted from the results obtained from the machine learning algorithms used to detect kidney disease.

Firstly, it is clear that AdaBoost is the best-performing algorithm overall, achieving a perfect accuracy score of 1.0 and the highest precision, recall, and F1-score for detecting both normal and kidney cases. This suggests that AdaBoost is the most suitable algorithm for detecting kidney disease based on the diagnostic measurements included in the dataset.

Secondly, it can be observed that Random Forest, RBF SVM, and Gaussian Process also achieved high accuracy scores of 0.9875, with RBF SVM and Gaussian Process achieving near-perfect precision, recall, and F1-scores. This indicates that these algorithms are also well-suited for detecting kidney disease.

On the other hand, Naïve Bayes and QDA were observed to have the lowest performance for all metrics, indicating that they may not be the best choice for detecting kidney disease based on the diagnostic measurements included in the dataset.

C. *Interpretation of the Results and the Implications*

The results of this study indicate that machine learning algorithms can effectively detect kidney disease based on specific diagnostic measurements. AdaBoost had the highest accuracy, precision, recall, and F1-score among the ten algorithms compared. This means that AdaBoost had the highest overall performance in detecting both positive and negative cases, accurately identifying true positives, and minimizing false positives and negatives.

On the other hand, Naïve Bayes and QDA had the lowest performance for all metrics, indicating that they

may not be suitable for detecting kidney disease based on this dataset. It is also interesting to note that some algorithms performed well in some metrics but poorly in others, such as Linear SVM having high precision but low recall.

These findings have important implications for healthcare professionals, as machine learning algorithms can potentially assist in the early detection of kidney disease and improve patient outcomes. However, further research is needed to validate the performance of these algorithms in more extensive and diverse datasets and assess their practicality and feasibility in clinical settings.

D. Comparison to Previous Studies

In this study, we compared the performance of ten machine learning algorithms for detecting kidney disease using four evaluation metrics: accuracy, precision, recall, and F1-score. Our findings indicated that AdaBoost had the highest performance across all evaluation metrics with perfect scores, while QDA had the lowest performance.

Compared to previous studies, our results are consistent with those that have reported high accuracy and F1-score for ensemble methods such as AdaBoost and Random Forest. For instance, Qin et al. [5] found that Random Forest achieved the best performance with 99.75% diagnosis accuracy in detecting kidney disease. Similarly, David et al. [7] found that ensemble methods such as IBK and random tree classification techniques were the best-performing classifiers in predicting diabetic kidney disease.

However, some studies have reported different findings. For example, Chowdhury et al. [9] found that the RF classifier model exhibited the best performance with 0.96 (±0.01) accuracy, 0.98 (±0.01) sensitivity, and 0.93 (±0.02) specificity. Meanwhile, our study found that AdaBoost had perfect scores for all evaluation metrics, indicating its superior performance compared to other algorithms.

Our study also observed that some algorithms, such as Linear SVM and Naïve Bayes, had lower recall values, indicating that these algorithms had difficulty identifying true positives. In contrast, AdaBoost and Random Forest had perfect recall values, indicating that these algorithms could detect all true positive cases.

Overall, comparing our results to previous studies suggests that the performance of machine learning algorithms for detecting kidney disease can vary depending on the specific algorithms and evaluation metrics used. Our study adds to the existing literature by comprehensively comparing multiple machine learning algorithms for kidney disease detection using a larger dataset.

E. Study Limitations and Future Research

Several limitations to our study should be acknowledged. First, our dataset was obtained from a single source, which may limit the generalizability of our findings to other populations. Second, the dataset only included a limited number of features, which may have limited the performance of some of the machine learning algorithms. Third, we used a fixed train-test split, which may have influenced the performance of some of the algorithms. Finally, we only evaluated a limited number of machine learning algorithms, and other algorithms could perform better.

To address these limitations, future studies could consider using larger and more diverse datasets from multiple sources to increase the generalizability of their findings. Additionally, future studies could consider using more advanced feature selection and engineering techniques to identify more informative features for prediction. Furthermore, it would be useful to investigate the impact of different train-test split ratios on the performance of the algorithms. Finally, future studies could consider evaluating a wider range of machine learning algorithms, including newer algorithms that have not yet been extensively studied in the context of kidney disease detection.

While our study provides valuable insights into the performance of several machine learning algorithms for kidney disease detection, several limitations should be addressed in future research. Addressing these limitations could help to improve the accuracy and generalizability of machine learning algorithms for kidney disease detection and ultimately improve patient outcomes.

V. CONCLUSION

In conclusion, using a larger dataset, our study compares multiple machine learning algorithms for kidney disease detection. The results demonstrate that several machine learning algorithms, including AdaBoost, Random Forest, and RBF SVM, have high accuracy, precision, recall, and F1-score in detecting kidney disease.

This study has important implications for healthcare providers, who can use these algorithms to develop more accurate and efficient methods for detecting kidney disease in patients. By integrating machine learning algorithms into decision support systems and screening programs, healthcare providers can improve patient outcomes and reduce the burden of kidney disease on individuals and healthcare systems.

Our study also contributes to the broader field of machine learning by suggesting that machine learning has potential applications in healthcare but has not been widely used in healthcare. As new algorithms and techniques are developed, it will be essential to continue to evaluate their performance and effectiveness in detecting kidney disease.

While this study provides valuable insights into the effectiveness of different machine learning algorithms for kidney disease detection, it is not without limitations. The study only used one dataset, and the results may differ with other datasets or populations. This study did not address potential biases or ethical considerations in using machine learning algorithms for medical diagnosis.

In light of these limitations, future research should continue to explore the effectiveness of different machine learning algorithms for kidney disease detection using diverse datasets and populations. Addressing potential biases and ethical considerations in using

machine learning algorithms for medical diagnosis is essential.

Overall, this study demonstrates the potential of machine learning algorithms for improving kidney disease detection and treatment, highlighting the importance of ongoing research and development.

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