

COMPARATIVE ANALYSIS OF MACHINE LEARNING ALGORITHMS WITH PRINCIPAL COMPONENT ANALYSIS FOR BREAST CANCER PREDICTION

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Abstract

Breast cancer is the leading cause of cancer death in Indonesia and globally, making early detection crucial. This study aims to compare the performance of Machine Learning algorithms (K-Nearest Neighbor/KNN, Support Vector Machine/SVM, Logistic Regression, Random Forest, and Decision Tree) in predicting breast cancer types using the Wisconsin Breast Cancer dataset. This dataset consists of 569 samples and is divided into training and testing sets using an 80:20 ratio. Evaluation methods include accuracy, precision, recall, F1-Score, and dimensionality reduction impact analysis using Principal Component Analysis (PCA). This study contributes by providing a comparative evaluation of several machine learning algorithms before and after PCA implementation. The results show that Random Forest achieved the highest accuracy (0.97) before PCA implementation but experienced a moderate decrease (0.94) after dimensionality reduction. KNN showed the highest consistency, maintaining a stable accuracy of 0.94 both before and after PCA. This study concludes that Random Forest is the most effective algorithm when using the full feature set, while KNN shows greater stability after dimensionality reduction, thus this study recommends KNN as a reliable solution to support accurate and efficient breast cancer diagnosis and early detection.

Keywords: Breast Cancer, Machine Learning, Early Detection, Principal Component Analysis.

1. INTRODUCTION

The development of digital technology in the last decade has brought significant progress in many fields, including machine learning. Machine learning can process large-scale data for prediction, classification, and automatic pattern recognition across domains such as healthcare, finance, manufacturing, and cybersecurity (Sarker, 2021). Its principal advantage is the ability of learning algorithms to adapt to complex data and identify patterns that may be difficult to specify manually.

In healthcare, machine learning can support diagnosis, prognosis, and treatment decisions by identifying patterns in complex clinical data (Rajkomar et al., 2019). This capability is particularly relevant to breast cancer, for which timely detection is essential. Globally, breast cancer was the most frequently diagnosed cancer among women and the leading cause of cancer death among women in 2022 (Bray et al., 2024). The disease also affects multiple dimensions of patients' lives, including physical functioning, emotional well-being, social relationships, and pain-related quality of life (Ośmiałowska et al., 2021). In Indonesia, the GLOBOCAN 2022 estimates recorded 66,271 new breast cancer cases, representing 16.2% of all new cancer cases, with age-standardized incidence and mortality rates of 41.8 and 14.4 per 100,000 women, respectively (Bray et al., 2024).

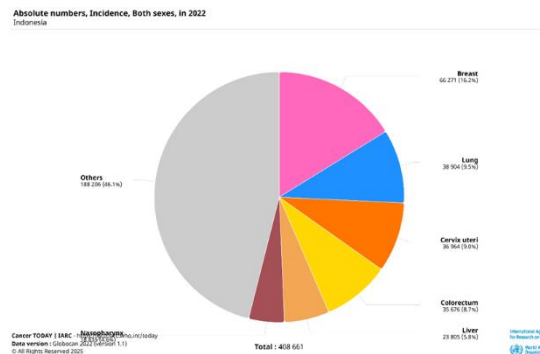


Figure 1. Cancer statistics in Indonesia. Source: Adapted from Bray et al. (2024).

Delayed diagnosis and treatment remain important contributors to unfavorable breast cancer outcomes. A recent meta-analysis found progressively higher mortality risks as treatment delays increased, with each additional four-week delay associated with more than a 10% increase in the hazard of death (Ungvari et al., 2026). Late detection can therefore limit treatment options and reduce the likelihood of favorable outcomes. The complexity of medical data used to identify and classify cancer cells also creates challenges for conventional diagnostic systems. These challenges motivate the use of intelligent computational methods, including machine learning, to support early detection.

Machine learning algorithms such as K-Nearest Neighbor (KNN), Random Forest, Support Vector Machine (SVM), Logistic Regression, and Decision Tree have been widely applied to disease classification and prediction. Comparative studies using breast cancer data show that performance depends on preprocessing, feature reduction or selection, model choice, and parameter optimization. Dhahri et al. (2019) evaluated several classifiers and preprocessing strategies for automated breast cancer diagnosis; Houfani et al. (2023) combined PCA with Logistic Regression on WDBC and WOBC datasets; and Al Reshan et al. (2023) investigated multi-model feature selection and ensemble learning on the WDBC dataset. These findings support evaluating several algorithms under the same data and experimental protocol.

Although numerous studies have applied machine learning to breast cancer prediction, many emphasize a particular classifier, feature-selection pipeline, or ensemble configuration. Evidence on how the same PCA transformation affects a broad set of conventional classifiers under an identical train-test protocol remains comparatively limited (Dhahri et al., 2019; Houfani et al., 2023; Al Reshan et al., 2023). A controlled comparison before and after PCA is therefore needed to distinguish changes attributable to dimensionality reduction from differences caused by data partitions or model settings.

Therefore, this study aims to compare the performance of five machine learning algorithms, namely K-Nearest Neighbor (KNN), Support Vector Machine (SVM), Logistic Regression, Random Forest, and Decision Tree, for breast cancer prediction using the Wisconsin Breast Cancer Dataset. In addition, this study evaluates the impact of Principal Component Analysis (PCA) on classification performance. The findings are expected to provide valuable insights into the effectiveness of dimensionality reduction techniques and assist in selecting the most appropriate machine learning algorithm for breast cancer prediction. Furthermore, the results may contribute to the development of more accurate and efficient decision-support systems for early breast cancer detection.

2. RESEARCH METHODS

This study uses a systematic approach consisting of five main stages, namely: data collection, data pre-processing, data extraction, machine learning model creation, and model testing as in Figure 2.

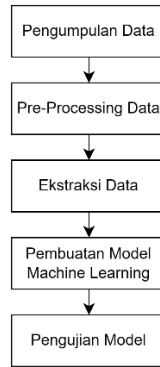


Figure 2. Research method model

2.1 DATA COLLECTION

The dataset used in this study was obtained from the Wisconsin Breast Cancer Dataset, available on the Kaggle platform. This dataset consists of 569 samples with 30 numerical features extracted from digitized images of fine needle aspirate (FNA) of breast masses. The target variable classifies each sample as benign (357 samples, 62.7%) or malignant (212 samples, 37.3%), resulting in a moderately imbalanced class distribution. The target variable classifies each sample as benign or malignant. This dataset was chosen because it is widely used as a benchmark for breast cancer prediction studies and provides balanced and reliable data for evaluating machine learning algorithms.

2.2 DATA PRE-PROCESSING

Data preprocessing was performed to improve data quality before model training. The preprocessing stage included checking for missing values and duplicate records, encoding the target class into numerical values, and standardizing the feature values using StandardScaler. Standardization was applied because several machine learning algorithms, such as K-Nearest Neighbor (KNN) and Support Vector Machine (SVM), are sensitive to differences in feature scales. The processed dataset was then divided into training and testing sets using an 80:20 ratio

2.3 DATA EXTRACTION

Principal Component Analysis (PCA) was applied as a feature-extraction technique to reduce dimensionality while retaining the dominant variance in the original variables. PCA transforms correlated features into orthogonal principal components ordered by the amount of variance they explain (Abdi & Williams, 2010). In this study, components were retained until they accounted for 90% of the cumulative explained variance. This approach was used to reduce computational complexity and redundant information and to evaluate the effect of dimensionality reduction on classifier performance.

2.4 MACHINE LEARNING MODELS

Five machine learning algorithms were implemented in this study, namely K-Nearest Neighbor (KNN), Support Vector Machine (SVM), Logistic Regression, Random Forest, and Decision Tree. Each algorithm was trained using the same training dataset and evaluated using the same testing dataset to ensure a fair comparison.

2.5 MODEL TESTING

The trained models were evaluated using the testing dataset. Model performance was assessed using a confusion matrix and four evaluation metrics: accuracy, precision, recall, and F1-score. These measures describe complementary aspects of binary classification performance and should be interpreted together, particularly when class distributions are unequal (Chicco & Jurman, 2020; Dhahri et al., 2019).

1. Accuracy: Accuracy measures the proportion of all observations that are correctly classified. It is calculated as the number of correct positive and negative predictions divided by the total

number of observations (Chicco & Jurman, 2020). The accuracy value is obtained using Equation (1):

$$accuracy = \frac{TP+TN}{TP+TN+FP+FN} \times 100\% \quad (1)$$

Information:

TP = True Positive

TN = True Negative

FN = False Negative

FP = False Positive

2. Precision: Precision is the proportion of observations predicted as positive that are actually positive (Chicco & Jurman, 2020). It is calculated as the number of true positives divided by the sum of true positives and false positives. The precision value is obtained using Equation (2):

$$precision = \frac{TP}{TP+FP} \times 100\% \quad (2)$$

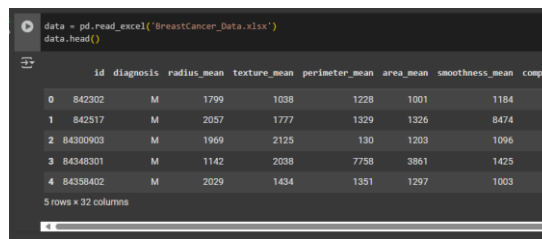
3. Recall: Recall is the proportion of actual positive observations correctly identified by the model (Chicco & Jurman, 2020). It is calculated as the number of true positives divided by the sum of true positives and false negatives. The recall value is obtained using Equation (3):

$$recall = \frac{TP}{TP+FN} \times 100\% \quad (3)$$

3. RESULTS AND DISCUSSION

3.1 DATASETS

Once the file is loaded, the dataset can be briefly visualized using the head() function. This function displays the first few rows of the dataset, making it easier for users to understand the data structure and its initial content before proceeding to further analysis stages as shown in Figure 3.

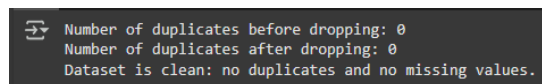


	id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean
0	842302	M	1799	1038	1228	1001	1184	
1	842517	M	2057	1777	1329	1326	8474	
2	84300903	M	1969	2125	130	1203	1096	
3	84348301	M	1142	2038	7758	3861	1425	
4	84338402	M	2029	1434	1351	1297	1003	

Figure 3. Dataset sample

3.2 DATA PREPROCESSING

The first step is to remove duplicate data to avoid repeated information that can affect the model results. Next, checks are made for empty values that can appear due to input errors or missing data. In this dataset, it was found to be free from duplication and empty as in Figure 4.



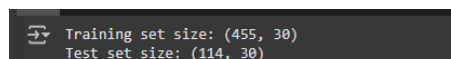
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Number of duplicates before dropping: 0
Number of duplicates after dropping: 0
Dataset is clean: no duplicates and no missing values.

```

Figure 4. Cleaning Results

After cleaning, label encoding is performed to convert categorical data into numeric data so that it can be processed by the machine learning model. The dataset is then divided into training data and test data with a proportion of 80:20 as in Figure 5, to ensure that the model is trained and tested objectively. The final step is scaling, using a method such as StandardScaler to standardize the scale of all features. This is important so that the model works optimally and fairly between features.



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Training set size: (455, 30)
Test set size: (114, 30)

```

Figure 5. Train Test Split

3.3 DATA EXTRACTION

After the data is standardized, dimension reduction is performed using Principal Component Analysis (PCA). PCA aims to simplify the number of features without losing important information, making the classification process faster and more efficient.

With a reduction of 90%, the PCA transformation produces 24 principal components, which are linear combinations of the original features. Each row in the PCA output data represents one sample in a lower-dimensional space, while maintaining the principal variance of the original dataset as shown in Figure 6..

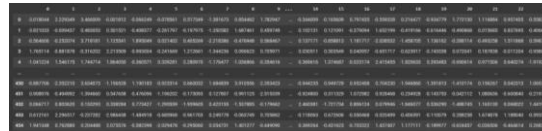


Figure 6. PCA transformation

3.4 IMPLEMENTATION OF ML MODEL

All algorithms were implemented using their default scikit-learn parameters: KNN with K=5 and Euclidean distance, SVM with RBF kernel and C=1.0, Logistic Regression with L2 regularization and C=1.0, Random Forest with 100 estimators, and Decision Tree with criterion='entropy'.

1. Before Reduction
 - a. KNN: The model evaluation results show very good performance with an accuracy of 94%. From the confusion matrix, it can be seen that out of 71 class 0 samples, 68 were correctly classified, while 3 were misclassified. For class 1, out of 43 samples, 39 were correctly classified and 4 were misclassified. The precision, recall, and F1-score values are each 0.94, indicating that the model is able to produce consistent and balanced predictions as shown in Figure 7.

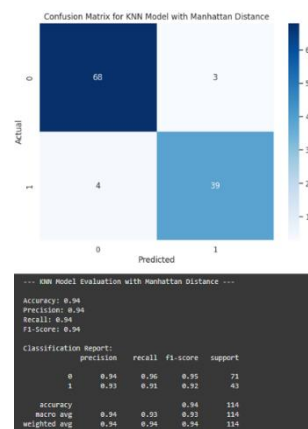


Figure 7. KNN confusion matrix before reduction.

- b. SVM: The results of the SVM model evaluation before showed quite high classification performance with an accuracy of 92%. Based on *confusion matrix* shown in Figure 8, from 71 samples of class 0, 66 were classified correctly and 5 were incorrect. While for class 1, from 43 samples, 39 were classified accurately and 4 were incorrect. The precision, recall, and F1-score values were each 0.92, indicating that the model has a balanced prediction performance.

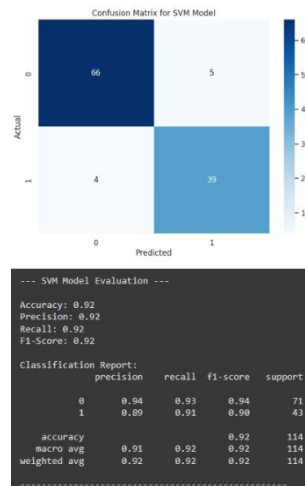


Figure 8. SVM confusion matrix before reduction

- c. *Logistic Regression*: The results show excellent performance with an accuracy of 93%. From the confusion matrix in Figure 9, it can be seen that the model successfully classified 67 out of 71 class 0 samples correctly, while 4 were incorrect. For class 1, 39 out of 43 samples were classified correctly and 4 were incorrect. The precision, recall, and F1-score values each reached 0.93, reflecting the balance between the accuracy and completeness of the model in making predictions. Overall, the model *Logistic Regression* shows high effectiveness in classification even though it still uses full-dimensional data.



Figure 9. LR confusion matrix before reduction

- d. *Random Forest*: The results show excellent classification performance with accuracy, precision, recall, and F1-score of 97%. Based on *confusion matrix* In Figure 10, all 71 class 0 data were successfully classified correctly, while in class 1, there were only 3 misclassifications out of a total of 43 samples. The precision value for class 1 even reached 100%, indicating no errors in positive predictions. Overall, this model is able to distinguish classes very accurately and consistently, making it the highest performing model compared to other models that have been tested.

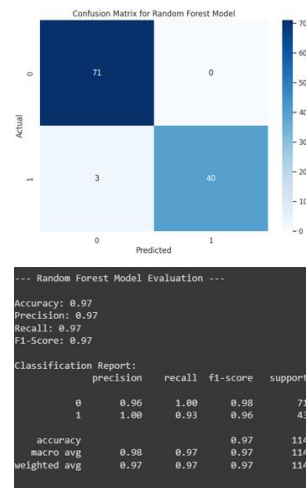


Figure 10. RF confusion matrix before reduction

- e. Decision Tree : Decision Tree model (C4.5) shows strong performance with accuracy, precision, *recall*, dan *F1-score* by 94%. Based on the confusion matrix in Figure 11, out of a total of 114 data, only 7 data were misclassified, consisting of 2 class 0 data that were misclassified as class 1, and 5 class 1 data that were misclassified as class 0. This model has good ability in detecting both classes, with class 0 recall of 97% and class 1 of 88%. High precision in both classes (93% and 95% respectively) indicates that the model's prediction results tend to be right on target.

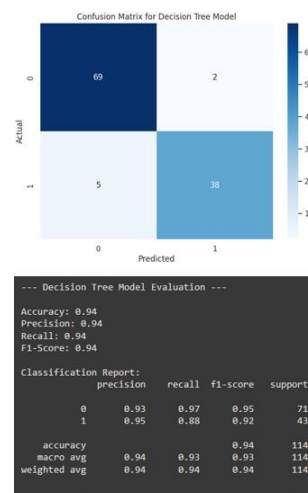


Figure 11. Confusion matrix C45 before reduction

2. After Reduction

- a. KNN: The results of the KNN model evaluation after applying PCA, obtained an accuracy of 94%, which shows that the model is able to classify data with a low error rate. Based on confusion matrix in Figure 12, shows that from a total of 71 class 0 samples, 69 were classified correctly and only 2 were incorrect. Meanwhile, from 43 class 1 samples, 38 were classified correctly and 5 were incorrect. The value precision, recall, dan F1-score each of 0.94, indicating that the model has a balanced performance in terms of prediction accuracy and completeness. Overall, these results indicate that dimensionality reduction using PCA successfully retains important information. in data and improve classification efficiency without sacrificing prediction quality. KNN maintained stable performance before and after PCA because the dimensionality reduction preserved the most informative features while eliminating redundant information. As a distance-based algorithm, KNN benefits from a

reduced feature space, resulting in consistent classification performance even after PCA implementation

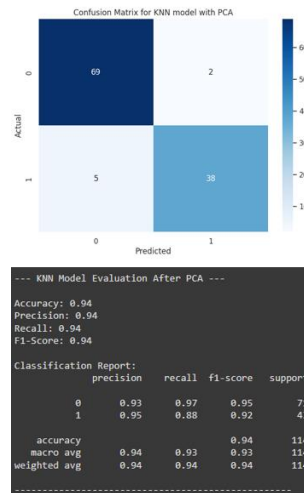


Figure 12. KNN confusion matrix after reduction.

- b. SVM: The results show that the classification performance remains consistent with an accuracy of 92%, the same as before dimensionality reduction. Based on *confusion matrix* In Figure 13, out of 71 class 0 samples, 66 were classified correctly and 5 incorrectly, while out of 43 class 1 samples, 39 were classified accurately and 4 incorrectly. The precision, recall, and F1-score values each remained at 0.92, indicating that the application of PCA did not degrade the model's performance. Thus, the use of PCA in the SVM model is able to maintain the quality of predictions while providing the potential for better computational efficiency.

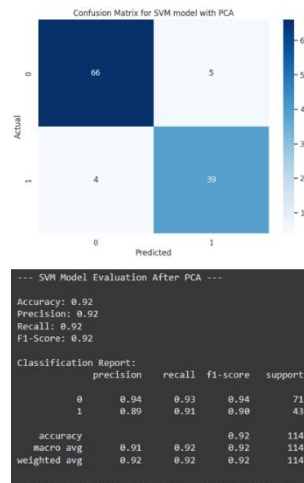


Figure 13. SVM confusion matrix after reduction.

- c. *Logistic Regression*: The results show strong classification performance with an accuracy of 92%, only slightly lower than before reduction. The *confusion matrix* in Figure 14 shows that out of 71 class 0 samples, 66 were classified correctly and 5 were incorrect. For class 1, 39 out of 43 samples were classified correctly and 4 were incorrect. The precision, recall, and F1-score values remained high at 0.92, indicating that dimensionality reduction did not significantly reduce the model's ability to recognize patterns. This indicates that PCA successfully simplified the data without sacrificing accuracy substantially

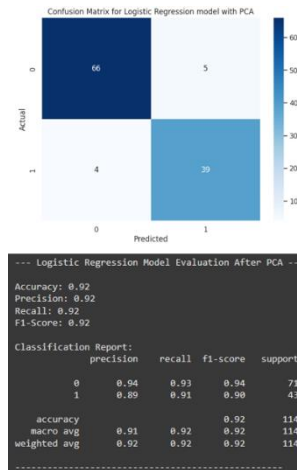


Figure 14. LR confusion matrix after reduction

- d. *Random Forest*: After PCA application, the performance of the Random Forest model decreased slightly with *accuracy*, *precision*, *recall*, and *F1-score* of 94%. Based on the confusion matrix in Figure 15, all 71 class 0 data were still correctly classified, but there was an increase in misclassification in class 1, namely 7 data that were mispredicted. However, the precision for class 1 remained high at 100%, indicating that all positive predictions were correct. The decrease in the recall value in class 1 from 93% to 84% reflects that some positive data were not detected after dimensionality reduction. This indicates that although PCA helps efficiency, it can reduce the model's sensitivity to minority classes. Random Forest achieves the highest classification accuracy before PCA because it combines multiple decision trees through an ensemble learning approach, reducing overfitting and improving generalization performance.

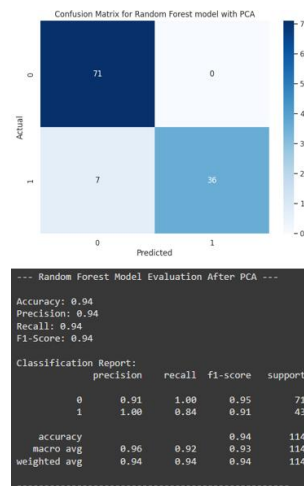


Figure 15. RF confusion matrix after reduction

- e. *Decision Tree* : The *Decision Tree* model (C4.5) shows strong performance with accuracy, precision, recall, and F1-score of 89%. Based on the confusion matrix in Figure 16, out of a total of 114 data, only 13 data were misclassified, consisting of 6 class 0 data misclassified as class 1, and 5 class 1 data misclassified as class 0. This model experienced a decrease in ability but remained good at detecting both classes, with a recall of class 0 of 92% and class 1 of 84%. The high precision in both classes (90% and 86% respectively) indicates that the model's prediction results tend to be on target. Decision Tree experienced a decrease in performance after PCA because it relies heavily on the original feature distribution to determine optimal splitting rules. The dimensionality reduction process may have removed information that was important for constructing accurate decision boundaries.

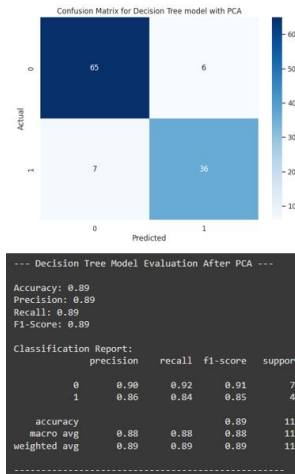


Figure 16. Confusion matrix Decision Tree after reduction

3.5 EVALUATION

Comparison of Evaluation Before Reduction:

Evaluation of five machine learning algorithms Table 1 shows that Random Forest has the best performance with *accuracy*, *precision*, *recall*, and *F1-score* scores of 0.97. KNN and *Decision Tree* C4.5 follow with a score of 0.94, followed by Logistic Regression (0.93) and SVM (0.92). These results confirm that Random Forest is the best in data classification, while other algorithms also show good performance with slight differences.

Table 1. Comparison of ML model performance before reduction

ML Algorithm	Accuracy	Precision	Recall	F1-Score
KNN	0.94	0.94	0.94	0.94
SVM	0.92	0.92	0.92	0.92
Logistic Regression	0.93	0.93	0.93	0.93
Random Forest	0.97	0.97	0.97	0.97
Decision Tree	0.94	0.94	0.94	0.94

1. Evaluation Comparison After Reduction: After the implementation of dimensionality reduction, the performance of several models experienced a slight decrease as shown in Table 2. KNN and Random Forest maintained the highest accuracy at 0.94, followed by SVM and Logistic Regression with a value of 0.92. Meanwhile, Decision Tree C4.5 showed the most significant performance decrease with a score of 0.89 across all evaluation metrics. This indicates that not all models are equally robust to the feature reduction process..

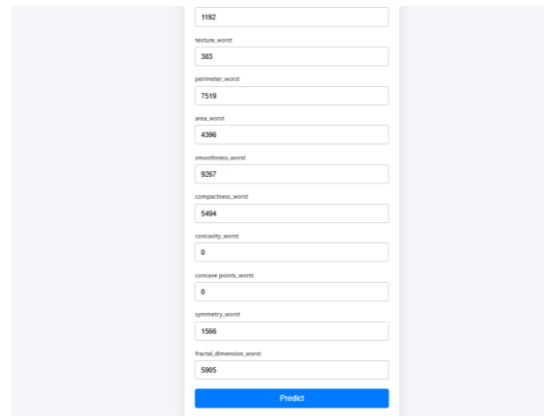
Table 2. Comparison of ML model performance after reduction

ML Algorithm	Accuracy	Precision	Recall	F1-Score
KNN	0.94	0.94	0.94	0.94
SVM	0.92	0.92	0.92	0.92
Logistic Regression	0.92	0.92	0.92	0.92
Random Forest	0.94	0.94	0.94	0.94
Decision Tree	0.89	0.89	0.89	0.89

3.6 BREAST CANCER PREDICTION SYSTEM

The application is designed to provide an easy-to-use interface for users. The web is shown to include essential elements such as an input form to receive data from the user and an area to display

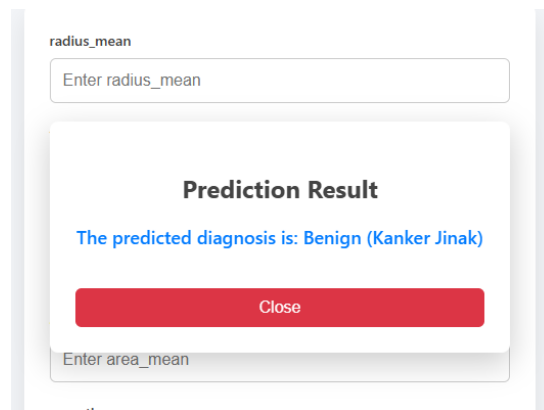
the prediction results. In the form, users can enter relevant data for breast cancer prediction, with each column clearly labeled for easy understanding as shown in Figure 17..



Field Label	Value
radius_mean	1182
texture_mean	383
perimeter_mean	7519
area_mean	4396
smoothness_mean	9267
compactness_mean	5494
concavity_mean	0
concave points_mean	0
symmetry_mean	1596
fractal_dimension_mean	9905

Figure 17. Web View

After filling out the form, the user can click the “Predict” button to send the data to the server, which will trigger the KNN algorithm to make a prediction based on the input provided. The prediction results will be displayed in a pop-up card that appears after the prediction is made, allowing the user to quickly view the resulting diagnosis as shown in Figure 17. In addition, if there is an error in filling in the data or the prediction process, the application will display an informative error message.



radius_mean

Enter radius_mean

Prediction Result

The predicted diagnosis is: Benign (Kanker Jinak)

Close

Enter area_mean

Figure 18. Prediction Results

Overall, this application produces an efficient and accurate model for predicting breast cancer categories, which is expected to help in early detection and treatment of this disease. The combination of KNN with PCA in this application shows that classification techniques such as KNN allow for effective data processing, resulting in excellent performance in data classification. By utilizing the KNN algorithm, this application can provide accurate predictions based on user input, thus supporting efforts to increase awareness and treatment of breast cancer.

4. CONCLUSION

Based on the results of this study, it can be concluded that the application of machine learning algorithms for breast cancer prediction demonstrates excellent classification performance. All evaluated algorithms, namely K-Nearest Neighbor (KNN), Support Vector Machine (SVM), Logistic Regression, Random Forest, and Decision Tree, achieved classification accuracies above 0.89. The experimental results indicate that Random Forest obtained the highest accuracy (0.97) before the application of Principal Component Analysis (PCA), making it the most effective algorithm when using the complete feature set. In contrast, KNN maintained stable performance with an accuracy of 0.94 before and after PCA, demonstrating its robustness in reduced feature spaces. Meanwhile,

Decision Tree experienced the largest decrease in performance after PCA, indicating that its classification capability is more sensitive to dimensionality reduction.

This study contributes to the comparative evaluation of multiple machine learning algorithms and provides insights into the impact of PCA on breast cancer prediction performance. The findings may assist researchers and healthcare practitioners in selecting appropriate machine learning models to support accurate and efficient early breast cancer diagnosis.

Future research is recommended to investigate advanced machine learning techniques, ensemble learning methods, feature selection approaches, deep learning models, and Explainable Artificial Intelligence (XAI) to further improve prediction accuracy, model robustness, and model interpretability.

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