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Comparative Analysis of Machine Learning Model Performance for Classification of Edible or Non-edible Mushrooms

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ABSTRACT

Mushrooms provide significant nutritional benefits and play a crucial role in the global food industry. However, not all mushroom species are safe for consumption, as some contain toxic compounds that can cause severe poisoning and even death. Accurate identification is essential to differentiate between edible and poisonous mushrooms. Traditional classification methods relying on manual morphological identification are often inaccurate, especially when toxic and edible mushrooms have similar physical characteristics. Machine Learning (ML) technology offers an innovative solution to enhance classification accuracy and improve safety in mushroom consumption. This study compares the performance of three major classification algorithms—Random Forest, Logistic Regression, and Naïve Bayes—using an open dataset from Kaggle. The analysis was conducted using the KNIME platform, evaluating the algorithms based on accuracy, sensitivity, and computational efficiency. The results indicate that Random Forest achieved the highest accuracy at 98.90%, followed by Logistic Regression at 69.67% and Naïve Bayes at 55.46%. These findings highlight the superiority of ensemble methods in classification tasks. This research contributes to the development of a reliable ML-based mushroom classification system. However, limitations remain, such as the exclusion of other high-performance algorithms like Support Vector Machine and Artificial Neural Networks. Future studies may incorporate optimization techniques to improve model performance. Additionally, implementing this classification system into mobile or web-based applications could provide broader benefits by enabling quick identification of mushrooms, minimizing health risks, and improving consumer confidence in mushroom safety.

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INTRODUCTION

The nutritional advantages, economic significance, and contribution of mushrooms to food security have long been recognized. They are commonly used as nutritious food sources and are known for their bioactive qualities, including anti-inflammatory, antibacterial, and antioxidant activities (Özaltun & Sevindik,

2020), (Rodríguez-Fernández et al., 2024). They are also rich in protein, fiber, vitamins, and vital minerals. Globally, some mushrooms, such as Agaricus bisporus and Lentinula edodes (shiitake), are widely grown and contribute significantly to agricultural economies (Ernanda & Sumbari, 2021), (Frencis Matheos Sarimole & Ridad Diadi, 2022). However, many types of mushrooms are extremely toxic; therefore, not all of them are safe to eat. Hazardous substances found in poisonous mushrooms, like Agaricus xanthodermus and Amanita phalloides, can result in serious poisoning and occasionally even death (Samir et al., 2023), (Yohannes et al., 2022). The possibility of mushroom poisoning emphasizes how crucial accurate identification techniques are. Classifying mushrooms has traditionally depended on manual identification using morphological and visual characteristics as well as professional knowledge. However, these techniques are prone to mistakes, particularly when poisonous and edible mushrooms seem alike (Rahmadhani & Marpaung, 2023). As interest in using technology to solve this problem has grown, machine learning (ML)-powered automatic classification systems have been developed. Convolutional neural networks (CNNs), support vector machines (SVMs), and random forest are examples of machine learning (ML) models that have demonstrated exceptional promise in the analysis of intricate mushroom datasets, correctly differentiating between species according to their morphological and biochemical traits (Hayami et al., 2022), (Villarroel Ordenes & Silipo, 2021).

Numerous obstacles still exist in spite of notable advancements in machine learning techniques for classifying mushrooms. The great diversity of mushroom species is one of the main challenges, making the creation of generalized models more difficult. Classification algorithms face difficulties due to the morphological similarities between hazardous and edible species as well as differences in environmental variables (Yohannes et al., 2022), (Zatadinia & Bhakti, 2024). The nonlinear correlations present in mushroom datasets are frequently difficult for traditional machine learning models like logistic regression and naive bayes to capture, which lowers accuracy and reliability (Rahmadhani & Marpaung, 2023), (Hayami et al., 2022). The dearth of thorough research that methodically analyze the performance of various ML algorithms under uniform conditions is another serious problem. CNNs' scalability in resource-constrained environments is limited by their computational complexity, despite their excellent accuracy in mushroom classification tasks (Villarroel Ordenes & Silipo, 2021). However, despite their computational efficiency, simpler models like Naive Bayes might not be able to handle the complexity of various datasets (Hayami et al., 2022). Additionally, the adoption of ML solutions in real-world contexts is hampered by the absence of an easy-to-use, standardized platform for creating and comparing these models. These constraints can be overcome with the help of tools like KNIME, which speed up the creation and assessment of ML workflows (Zatadinia & Bhakti, 2024).

This research can address the difficulties in classifying mushrooms by thoroughly examining three well-known machine learning algorithms: Random Forest, Naive Bayes, and Logistic Regression. This study's primary goal is to ascertain whether mushrooms are toxic or edible. This study aims to address important concerns about the efficacy and efficiency of using machine learning (ML) algorithms by leveraging the KNIME analytics platform. ln order for the research to pinpoint machine learning algorithms that exhibit a high degree of precision in differentiating between toxic and edible mushrooms. This entails examining the algorithm's capacity to reliably generate accurate predictions even in the face of intricate and diverse dataset settings.

A number of criteria, including computational efficiency, sensitivity (recall), and precision, will be used to compare the algorithms' performances. Therefore, the evaluation also takes into account how well these algorithms manage datasets with a variety of morphological characteristics and how well each method strikes a balance between classification accuracy and the necessary processing power. The process of creating, testing, and analyzing ML model outputs can be made simpler by using KNIME as the primary tool.The results of this work are intended to add to the expanding corpus of research on machine learning applications in food safety, specifically in lowering the risks of mushroom poisoning. The study also aims to give researchers and practitioners practical insights so they may create categorization systems that are more dependable and effective.

In recent years, various studies worldwide have been conducted on classification and predictive analytics across multiple fields. Classification techniques play a crucial role in predicting data values based on known information from various sources (Haksoro & Setiawan, 2021). Several prior studies have implemented classification methods to generate predictions in different research contexts.

For instance, the study in (Zatadinia & Bhakti, 2024) applied six different Machine Learning algorithms—Decision Tree, SVM, KNN, Random Forest, Logistic Regression, and Naïve Bayes—to analyze diabetes prediction in humans. Meanwhile, the research in (Samir et al., 2023) utilized algorithms such as Random Forest, Naïve Bayes, Support Vector Machines (SVM), and K-Nearest Neighbors to identify the likelihood of breast cancer in women. Another study, as mentioned in (Fathurrohman et al., 2024), explored the application of Data Mining techniques to extract information from raw student data using various algorithms, including KNN, Naïve Bayes, and Decision Tree.

In the study (Hayami et al., 2022) titled "Behavioral Malware Detection Using Naïve Bayes Classification Techniques", it was found that data mining is highly effective in detecting malware. Classification based on malware behavioral characteristics can be used as a strategy in developing behavior-based antivirus

systems.

Another study in (Ernanda & Sumbari, 2021) evaluated seven different algorithms, including Decision Table, Random Forest (RF), Naïve Bayes (NB), Support Vector Machine (SVM), Neural Networks (Perceptron), JRip, and Decision Tree (J48), utilizing the Waikato Environment for Knowledge Analysis (WEKA) tool for Machine Learning on a diabetes dataset. The study found that key factors influencing the model included training time and accuracy, while kappa statistics and Mean Absolute Error (MAE) also contributed to performance evaluation. Therefore, Machine Learning algorithms must achieve high accuracy and minimal error to be effectively applied in predictive machine learning.

Additionally, survey results from study (Made Susun & Darsini, 2023) indicated that supervised learning algorithms such as Support Vector Machines (SVM), K-Nearest Neighbour (KNN), Naïve Bayes, Decision Trees (DT), Random Forest (RF), and ensemble models are the most frequently used approaches in predicting cardiovascular diseases.

The study (Frencis Matheos Sarimole & Ridad Diadi, 2022), titled "Behavioral Features for Mushroom Classification", focused on classifying mushrooms based on characteristics such as shape, surface, and cap color, as well as gills and stems. Other analyzed aspects included smell, population, and habitat. In this study, Principal Component Analysis (PCA) was used to determine the best features for classification experiments using Decision Tree (DT). The findings revealed that the J48 classification model resulted in 23 leaves with a tree size of 28.

In study (Yohannes et al., 2022), various data mining algorithms such as ID3, CART, and Hoeffding Tree (HT), all based on Decision Tree methods, were examined. Among these, Hoeffding Tree demonstrated the best performance with the highest accuracy, faster training time, and the lowest error rate compared to ID3 and CART.

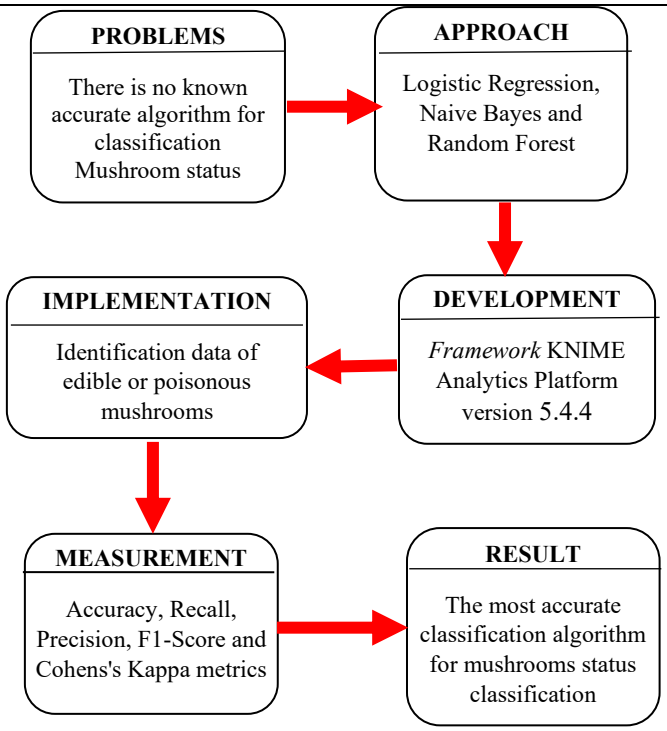
Study (Rahmadhani & Marpaung, 2023) focused on developing a mushroom classification technique based on texture features using a Machine Learning approach. The results indicated that the proposed method achieved an accuracy of 76.6% using SVM as the primary classification algorithm. Furthermore, this algorithm outperformed other methods such as KNN, Logistic Regression, Linear Discriminant, Decision Tree, and ensemble classifiers.

In study (Harneni et al., 2024), the Decision Tree approach was implemented to develop a classification model distinguishing between edible and poisonous mushrooms. The evaluation results showed that combining the Information Gain technique with Random Forest produced the highest accuracy, reaching 94.19%.

RESEARCH METHOD

The design, execution, and data analysis of a research are conducted using a process known as research methodology. Initiation, linear model development, comparison of model test results, and analysis of classification results were used in this research. In addition to cleaning and preparing the data, the first phase involved determining which variables were most important in classifying mushrooms as edible or poisonous. In this research, researchers conducted a comparative analysis of three machine learning classification algorithms that belong to supervised learning including Logistic Regression, Naive Bayes and Random Forest. The Logistic Regression Classification Algorithm is used in this research because it is often used to analyze or identify data and is suitable for identification when the output of a data is binary. Can produce a high accuracy value of 93% with confusion matrix testing in accordance with research activities carried out by (Zatadinia & Bhakti, 2024) with the research title Identification of Consumable and Toxic Mushrooms Using the Logistic Regression Method. The next classification algorithm used in this research is the Naive Bayes Classification Algorithm. This classification algorithm can assume that each attribute value that affects the class value is independent of the attribute value that affects other class values. In research conducted by (Arslan et al., 2024) explaining the results of evaluation and confusion matrix, it can be seen that the model with naïve bayes categorical is the best with a large enough performance distance where the Categorical1 and Categorical2 models get 100% accuracy with 1 class prediction error 0 in the Categorical 2 model. Meanwhile, the Multinomial1 and Multinomial2 models obtained accuracy values of 84% and 85%. Then the Classification Algorithm used next is the Random Forest Classification Algorithm, where in this algorithm the decision variable is categorical. To implement Random Forest, the cost function used to evaluate binary separation is called the Gini Index. In research conducted by (Hayami et al., 2022) with the research title Prediction of Insufficient Accuracy for Mushroom Classification whether Poisonous or Eatable Food using Random Forest Training by comparing Logistic Regression to Improve Accuracy resulted in an accuracy of 92.82% for evidence that can be recognized poison with the base value of the next two tests is 0.001 ($p < 0.05$) with a confidence stretch. of 95%.

This research consists of several stages as shown in figure 1 research framework.



Source: Research Results (2025)

Figure 1. Research Framework

This research consists of several stages as shown in Figure 1 research framework. The problem in this research is that there is no known accurate algorithm for the classification of mushrooms that can be consumed or not. For this reason, an approach (model) is made, namely the Logistic Regression, Naive Bayes and Random Forest algorithms to solve the problem, then testing the performance of some of these methods is carried out. The test uses Accuracy, Recall, Precision, F1-Score and Cohens's Kappa metrics. To develop applications (development) based on the model created, the KNIME Analytics Platform version 5.4.4 is used. The stages in developing the model are described in the form of a workflow in Figure 1.

RESULTS AND DISCUSSION

A. Data Analysis

There are 54035 records of edible or poisonous mushroom data with the remark Edible or Poisonous obtained from https://www.kaggle.com/datasets/prishasawhney/mushroom-dataset. The attributes in this dataset include Cap Diameter, Cap Shape Gill Attachment, Gill Color, Stem Height, Stem Width, Stem Color, Season. These variables are used as independent variables in the classification model applied in this study. Specifically, Cap Diameter describes the size of the mushroom's hood diameter in certain units (e.g. cm or mm); Cap Shape describes the shape of the top of the mushroom including Bell-shaped, Convex, Flat, Umbonate, Sunken; Gill Attachment describes the way the mushroom's gill is attached to its stem including Free, Attached, Decurrent; Gill Color describes the color of the mushroom's gill, which can be a clue to species identification categorized as white, brown, black, red, yellow; Stem Height describes the height of the mushroom stem in certain units (e.g. cm or mm); Stem Width describes the width or diameter of the mushroom stem; Stem Color describes the color of the mushroom stem which can vary from white, brown, red, yellow, to other colors; Season describes the time or season when mushrooms usually grow, such as Spring, Summer, Autumn or Fall, and Winter. The variable Class is the target or label in this dataset, which contains two values - 0 or 1 - where 0 refers to edible and 1 refers to poisonous. These attributes play an important role in the classification process to assess the classification of edible or non-edible mushrooms in this study.

The following Figure 2 describes the sample data set used during testing.

#	RowID	cap-diameter Number (integer)	cap-shape Number (integer)	gill-attachment Number (integer)	gill-color Number (integer)	stem-height Number (double)	stem-width Number (integer)	stem-color Number (integer)	season Number (double)	class Number (integer)
1	Row0	1372	2	2	10	3.807	1545	11	1.804	1
2	Row1	1461	2	2	10	3.807	1557	11	1.804	1
3	Row2	1371	2	2	10	3.612	1566	11	1.804	1
4	Row3	1261	6	2	10	3.788	1566	11	1.804	1
5	Row4	1305	6	2	10	3.712	1464	11	0.943	1
6	Row5	1337	6	2	10	3.776	1520	11	0.943	1
7	Row6	1300	2	2	10	3.835	1563	11	1.804	1
8	Row7	1354	6	2	10	3.676	1532	11	0.888	1
9	Row8	1222	6	2	10	3.772	1476	11	0.943	1
10	Row9	1085	6	2	10	3.776	1581	11	0.888	1
11	Row10	1214	6	2	10	3.696	1524	11	1.804	1
12	Row11	642	6	2	10	0.286	1311	11	0.943	1
13	Row12	814	4	2	10	1.189	1681	11	0.943	1
14	Row13	550	4	2	10	0.549	1220	11	0.888	1
15	Row14	606	6	2	10	0.254	1239	11	0.943	1

Source: Research Results (2025)

Figure 2. Sample Data Set

B. Data Preprocessing

At this stage the Number To String node function in KNIME is used to convert numeric data (numbers) into data of type string (text). In this research, the attributes used include Cap Shape, Gill Attachment, Gill Color, Stem Color, Season and Class. The reason for choosing these attributes is because Classification must meet the requirements that each attribute must be nominal and numeric, while the target attribute or label must be nominal.

C. Model Selection

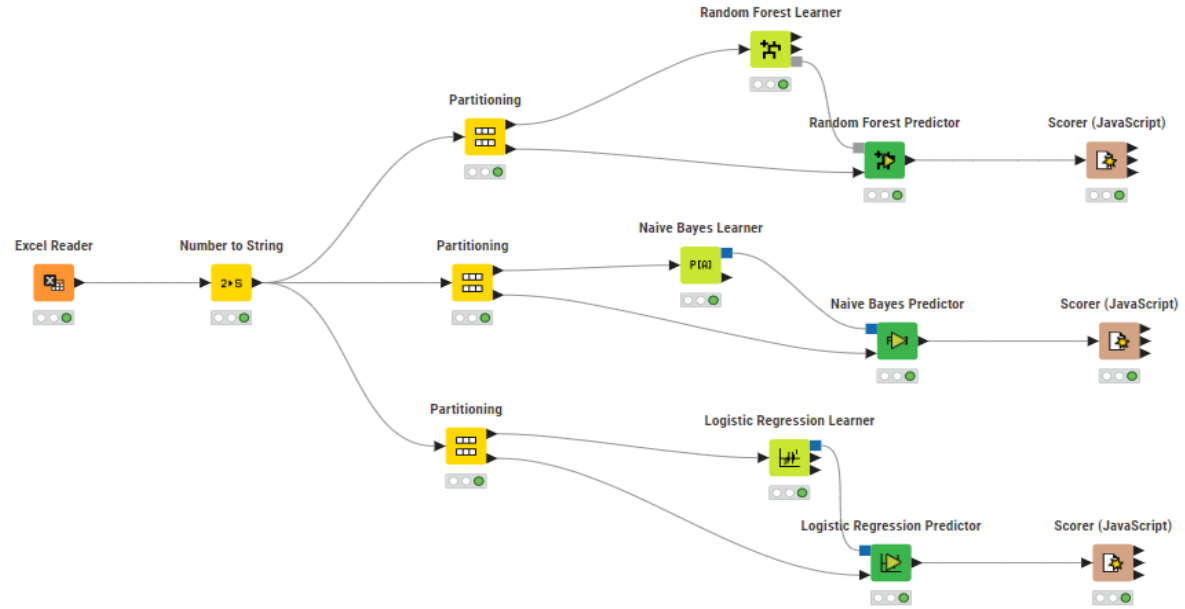
In this model selection stage, the algorithms used for testing are Logistic Regression, Naive Bayes and Random Forest algorithms to solve the problem, then testing the performance of several methods is carried out. The best model assessment is obtained from the performance value measured using various evaluation metrics, namely Accuracy, Recall, Precision, F1-Score and Cohens's Kappa. This comparison process makes it possible to determine the most suitable and effective algorithm to model the problem of classification of edible or non-consumable mushrooms with optimal accuracy and performance.

D. Data Splitting

After data pre-processing stage, the next step in developing a machine learning model is to divide the dataset into two main subsets: training and testing. Model development is to divide the dataset into two main subsets: training and testing. The training subset is used to train the model, while the testing subset serves to test the performance of the trained model. This division aims to evaluate the extent to which the model can perform an accurate classification on new data that has never been seen before. Activities in dividing dataset by allocating data for training, usually around 70-90%, and the rest is allocated for testing, around 10-30%. testing, ranging from 10-30%. These proportions may vary depending on complexity of the problem and the amount of data available. Based on this technique, the model can be trained with enough data to understand the general patterns and tested on a a separate subset to gauge its ability to perform classification on new data. on new data. This division of the dataset helps prevent overfitting and ensures that the model has good generalization. ensure that the model has good generalizability on data that has not been never seen before.

E. Model Development

In this stage, the proposed model was tested. Furthermore, evaluation and validation procedures are applied to obtain Accuracy, Recall, Precision, F1-Score and Cohens's Kappa values. Data processing and testing used KNIME Analytics Platform version 5.4.4. The model built is depicted in Figure 3.



Source: Research Results (2025)

Figure 3. The model built

Model development using KNIME involves various machine learning algorithms that each have specific nodes or components within the platform. Algorithms such as Random Forest, Naïve Bayes, and Logistic Regression have different nodes for each stage in the model development process. The process of training a model on a subset of training data with an algorithm involves hyperparameter adjustment, parameter tuning, and model iteration to improve performance and prediction accuracy. Figure 3 displays the three workflows of the edible or non-consumable mushroom classification model using KNIME Analytics Platform version 5.4.4.

At this stage of model development, the mushroom dataset is input using the Excel Reader node. Furthermore, the Number to String node is used to convert numeric value types into strings by involving attributes such as cap shape, gill attachement, gill color, stem color, season and class. The next stage is the algorithm testing stage. At this stage, each algorithm uses specific nodes, namely, Random Forest using Random Forest Learner and Predictor nodes, Naïve Bayes using Naïve Bayes Learner and Predictor nodes, Logistic Regression using Logistic Regression Learner and Predictor nodes. The results of the classification can be obtained by adding a scorer node to the Predictor node.

F. Model Validation

Machine learning models are trained repeatedly with varying parameters to achieve the highest accuracy. This helps to optimize the model and prevent overfitting. This process aims to ensure that the resulting model has optimal performance and is able to provide accurate classification on new data. The following Table 1 describes the performance comparison results of three machine learning algorithms used in this study, including Random Forest, Naïve Bayes, and Logistic Regression.

Table 1. Performance Comparison Results of Three Algorithms on Machine Learning

Algorithm	Accuracy	Recall	Precision	F1-Score	Cohens's Kappa
Random Forest	99,01%	0,98	0,99	0,98	0,98
Naïve Bayes	70,26%	0,68	0,66	0,67	0,40
Logistic Regression	74,95%	0,72	0,72	0,72	0,49

Source: Research Results (2025)

The test results of machine learning algorithms show different performance from the algorithms used. The following is a description of the test results as follows:

1. Random Forest has the highest accuracy rate of 99.01%, which indicates a high level of accuracy in classification. The high F1-Score of 0.98 shows a balance between precision with a value of 0.99 and recall which is worth 0.98. This indicates good performance in data classification.
2. Naïve Bayes shows an accuracy result of 70.26%, as well as an F1-Score of 0.67. The precision value is 0.66 and the recall value is 0.68. With these results the Naïve Bayes algorithm is ranked 3rd in this validation model.
3. Logistic Regression provides an accuracy result of 74.95%, as well as better F1-Score, precision, and recall compared to Naïve Bayes results. Based on the validation results of this model, the Logistic Regression algorithm occupies the 2nd position.

CONCLUSION

Based on the test results obtained from the application of three machine learning algorithms, Random Forest algorithm has the best performance with the highest accuracy of 99.01% and has very high Recall, Precision, F1-Score, and Cohens's Kappa values. Therefore, Random Forest can be considered as the best model of the three algorithms tested in this case study. In second place, the Logistic Regression algorithm produces an accuracy value of 74.95%, and has an F1-Score value of 0.72, a Recall value of 0.72, a Precision value of 0.72, and a Cohens's Kappa value of 0.49. In the third position, the Naïve Bayes algorithm has an accuracy value of 70.26%, an F1 Score value of 0.67, a precision value of 0.68, a Recall value of 0.68, and a Cohens's Kappa value of 0.40. However, this research is limited to using three classification algorithms (Random Forest, Naïve Bayes, and Logistic Regression), without trying other algorithms that could potentially provide higher performance, such as Support Vector Machine or Artificial Neural Network. In addition, this research has not used optimization algorithms such as Particle Swarm Optimization (PSO) or Gradient Boost to improve model performance. These research gaps indicate that further research on classification and optimization algorithms can contribute to the development of more accurate and reliable mushroom classification models. Therefore, future research is expected to overcome this limitation by using a more varied approach.

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