Leveraging the Power of MRMR in Machine Learning Models for Multi Class Classification of Rice to Promote Sustainable and Efficient Smart Farming

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Abstract. Rice variety classification is of significant importance in the agricultural domain since it allows for effective crop management, quality evaluation, and yield optimization. This research paper presents an intelligent system for automatic rice variety identification into multiple classes using machine learning techniques. The Maximum Relevance Minimum Redundancy (MRMR) attribute selection technique is used in the framework to discover the most important attributes from a large dataset, ensuring accurate and reliable classification. Various machine learning based classification techniques, including Decision Trees, K-Nearest Neighbors (KNN), Support Vector Machines (SVM), Ensemble methods, Neural Networks (NN), and Naive Bayes, are explored in their different variants.

Series of experiments were conducted on a real-time dataset featuring multiple rice varieties to evaluate the performance of each classifier based on metrics such as accuracy, precision, recall, and F1 score. The study explores the effectiveness of the proposed framework, revealing that Ensemble machine learning, SVM and Neural Networks emerge as the optimal classifiers, achieving an impressive accuracy rate of 99.8% in the multi-class classification of rice varieties. The proposed framework empowers farmers and researchers to make informed decisions in crop management, resource allocation, and ensuring food security in agricultural practices.

Keywords: Rice Variety Classification · Machine Learning Models · Maximum Relevance Minimum Redundancy · Feature Engineering

1 Introduction and Related Work

Agriculture is crucial to sustaining global food production and satisfying the rising demand for nutrient-rich crops [1, 2]. Rice is one of the most important staple cereals in the world, functioning as the main source of nutrition for a substantial population. Effective and precise classification of rice varieties is essential for a number of reasons [3, 4].

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It enables producers to make informed judgements about crop management practices, such as optimizing irrigation, fertilization, and pest control methods for specific rice varieties. This targeted approach can result in increased crop yields, decreased resource waste, and increased agricultural productivity overall. Second, accurate classification [5, 6] facilitates effective seed selection and breeding programmes, enabling the development of new rice varieties with desirable characteristics such as disease resistance, high yield potential, and enhanced nutritional content. In addition, precise classification of rice varieties facilitates market segmentation and quality control, ensuring that consumers receive the desired rice type and boosting both customer satisfaction and market competitiveness. Ultimately, the efficient and accurate classification of rice varieties contributes to sustainable agricultural practices, food security, and agricultural sector economic growth [7–9].

Classification techniques facilitate the precise identification and categorization of data based on their distinctive characteristics [10–14]. Researchers can efficiently classify data across diverse domains using machine learning algorithms, enabling efficient data analysis, pattern recognition, and accurate decision making [15–18]. In addition, machine learning algorithms provide potent classification capabilities for rice varieties. These algorithms are capable of analyzing vast quantities of data, identifying patterns, and deriving valuable insights. Researchers are able to precisely categorize rice varieties based on their distinct features and characteristics by leveraging machine learning [19].

Efficient rice classification relies on careful attention to key phases of the machine learning model workflow. Data collection includes gathering a worthy dataset that encompasses various attributes of rice varieties. Pre-processing techniques are applied to clean, normalize, and transform the data, ensuring its suitability for training. During the training phase, the model learns patterns and relationships from the labeled data, while the validation phase assesses its performance and fine-tunes parameters. Finally, the model is evaluated with previously unseen data to determine its generalizability. Each stage is critical for producing accurate and dependable rice classification findings, emphasizing the importance of careful thought and optimization throughout the process.

Decision Trees, KNN, SVM, Ensemble techniques, Neural Networks, and Naive Bayes are all commonly used for rice variety categorization. Decision Trees provide a hierarchical tree-like structure to give an organized method to decision-making. KNN classifies instances based on their closeness to neighboring data points. To divide various classes in the feature space, SVM employs a hyperplane. To increase accuracy, ensemble approaches integrate many classifiers. Neural networks are extremely sophisticated models that can learn complicated patterns. The Naive Bayes classifier is a probabilistic classifier based on the Bayes theorem. Researchers can determine the best strategy for accurate and efficient rice categorization by experimenting with different classifiers.

In addition to machine learning approaches, attribute selection [20–23] is critical for good rice classification. The goal of attribute selection techniques is to find the most relevant and informative characteristics in a huge dataset. The classification models can focus on the important traits that separate distinct rice types by picking the most discriminative qualities. As a result, model performance improves, computational complexity decreases, and interpretability improves [24–28]. Attribute selection strategies [29–31] aid in the removal of unnecessary or redundant characteristics, resulting in more accurate and efficient categorization. Researchers can optimize the classification process and gain relevant insights from the rice dataset by introducing attribute selection methods into the machine learning framework.

The main goal of this research is to investigate the best machine learning models and attribute selection strategies for reliable rice categorization. The study attempts to discover the models that perform the best in recognizing and categorizing rice types by studying several machine learning algorithms and their modifications. Furthermore, the study tries to identify the best attribute selection approach for efficiently capturing the fundamental traits and properties of the rice dataset. The outcomes of this study will give significant insights and direction for rice classification researchers and practitioners, allowing for more accurate and efficient classification methods.

2 Proposed Machine Learning-Based Rice Variety Recognizer

This paper presents ML-RVR (Machine Learning-based Rice Variety Recognizer), an intelligent framework designed to reliably classify rice varieties. The framework includes all of the essential phases of a machine learning model, including data collection, preprocessing, feature selection, model training, validation, and testing. By utilizing this comprehensive strategy, ML-RVR ensures that all essential facets of the classification process are considered. The Fig. 1 depicts the overall architecture of ML-RVR, highlighting its systematic approach to rice classification.

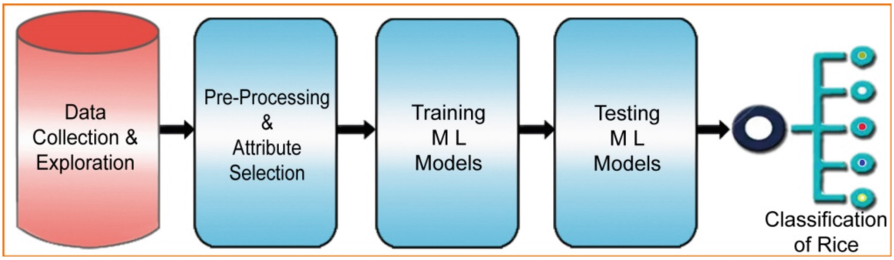

Fig. 1. Architecture of Proposed ML-RVR Model

2.1 Dataset Collection and Exploration

The ML-RVR considers a dataset collected from www.muratkoklu.com/datasets/, which has 106 attributes in total. These attributes are divided into three categories shown in Fig. 2 twelve morphological attributes, four shape based attributes derived from the morphological attributes, and ninety color attributes generated from five separate color spaces. Essential morphological attributes include area, perimeter, major axis length, minor axis length, eccentricity, and equivalent diameter. These attributes give useful information about the physical properties of rice grains. Furthermore, shape based attributes are computed based on the morphological attributes' area, major axis length, and minor axis length. These feature values indicate the pixel count of each rice grain, providing useful information for shape analysis. The color features include RGB-HSV Conversion, RGB-XYZ Conversion, RGB-Lab* Conversion, and RGB-YCbCr Conversion, among others. These properties capture the color characteristics of rice grains, allowing researchers to investigate the various color patterns displayed by different rice cultivars.

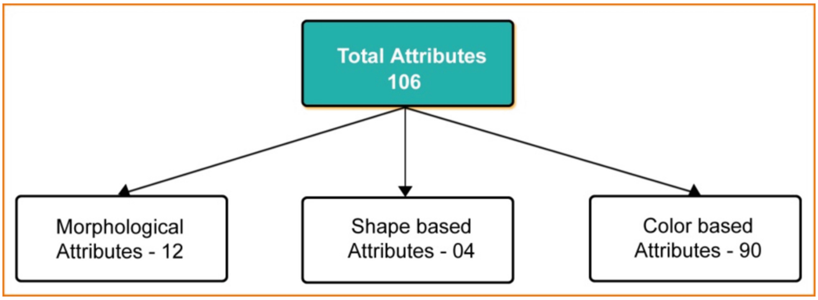

Fig. 2. Attributes of Collected Dataset

The dataset contains 75,000 tuples, with each rice class represented equally. Arborio, Basmati, Ipsala, Jasmine, and Karacadag are the five classes represented in the dataset as shown in Table 1 and Fig. 3.

Table 1. Available Classes in the Dataset

S. No.	Class	Shape	Length(max)	Width(max)
1	Arborio	Oval	6.35 mm	03.40 mm
2	Basmati	Long	11.50 mm	02.00 mm
3	Ipsala	Short	10.56 mm	05.50 mm
4	Jasmine	Cylindrical	07.00 mm	01.75 mm
5	Karacadag	Round	05.04 mm	03.50 mm

Arborio. Arborio is an Italian variety of short-grain rice distinguished by its distinctive oval shape and pure white color. The grains retain a firm and buttery texture after cooking, distinguishing it from other types of rice.

Basmati. Basmati is originating in the picturesque Indian Himalayan foothills, Basmati is a renowned aromatic long grain rice. It is highly esteemed for its fragrant aroma and subtle taste. In addition to being gluten-free and low in cholesterol, Basmati rice is a healthful option for those seeking a nutritious and flavorful rice option.

Ipsala. Ipsala derives its name from the small rural Turkish city of Ipsala, where it is produced extensively. Ipsala rice is notable for its wider grain width compared to other rice varietals, measuring approximately 4–5.5 mm in width on average. This distinguishing characteristic contributes to its unique culinary qualities and distinguishes it visually and texturally.

Jasmine. Jasmine rice is grown primarily in Thailand and Vietnam and is available in both white and brown hues. While Jasmine rice is prized for its fragrant aroma, it should be noted that it is not a particularly rich source of vitamins and minerals. However, its adaptability and delicate flavor make it a popular ingredient in a variety of dishes.

Karacadag. Karacadag rice shares grain width characteristics with Arborio rice. However, its length is significantly shorter than Arborio rice. This unique combination of characteristics lends Karacadag rice its distinctive identity and distinguishes it from other rice varieties.

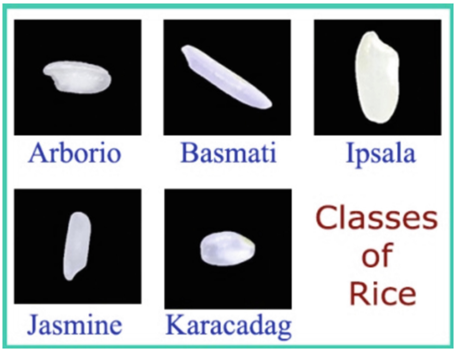

Fig. 3. Rice Varieties of Collected Dataset

The dataset is well-suited for training machine learning models for all five classes due to its balanced distribution of data across classes as shown in Fig. 4. This large dataset offers researchers with a valuable resource for developing and testing machine learning methods for rice variety detection.

The correlation matrix for the morphological attributes used in this investigation is shown in Fig. 5. The correlation matrix depicts the interrelationships and dependencies between the numerous morphological attributes used to identify rice varieties. A detailed examination of this matrix reveals that there is a significant and consistent association between the various qualities. This strong association shows that changes in one morphological attributes are frequently followed by changes in other aspects. Such a strong relationship between morphological qualities gives useful insights into the intrinsic properties of rice varieties and their distinguishing characteristics.

2.2 Data Pre-processing and Attribute Selection Method

Data pre-processing in ML-RVR entails transforming unstructured data into a format suitable for machine learning algorithms. This step attempts to resolve missing

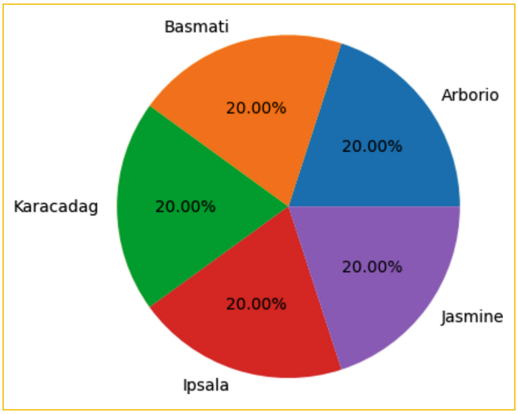

Fig. 4. Equal Distribution of Data across 5 Rice Classes

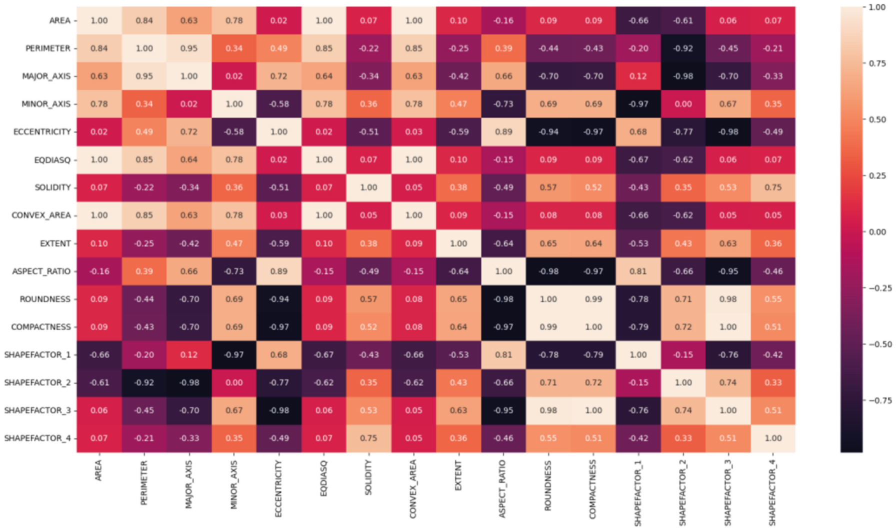

Fig. 5. Correlation Matrix of Morphological Attributes

values, remove outliers, and handle inconsistent data representation, normalizing or standardizing data in order to improve the quality and dependability of the dataset.

In the context of attribute selection, the MRMR method stands out as a powerful technique. ML-RVR employs MRMR that prioritizes selecting the most interesting and relevant qualities from a given dataset while minimizing redundancy. The MRMR technique takes a thorough approach to feature selection, taking into account both an attribute's relevance to the target variable and its redundancy with other features. MRMR assists in identifying a subset of characteristics that may effectively describe the data while minimizing excessive repetition by finding a balance between relevance and redundancy.

The employed MRMR algorithm 1 of ML-RVR is outlined below. This algorithm is used for attribute selection in order to classify five rice varieties based on a dataset containing 106 attributes.

Algorithm1: Application of MRMR to retrieve top-ranked features for ML-RVR
Input : The dataset containing 106 attributes and the corresponding class labels
Output : Top Ranked features by MRMR

Step.1 Calculate mutual information for morphological, shape-based, and color attributes with class labels.
Step.2 Rank the attributes based on their mutual information with the class labels. Separate the attributes into three groups: morphological, shape-based, and color. Rank the attributes in each group based on their relevance to the class.
Step.3 For each iteration:
  Step.3 a Compute the redundancy between each attribute and the features already selected in the corresponding group.
  Step.3 b Subtract the redundancy from the relevance for each attribute in each group.
  Step.3 c Choose the attribute with the highest MRMR score as the best feature from each group.
  Step.3 d Add the selected features from each group to the set of selected features.
  Step.3 e Remove the selected features from each group from the dataset.
Step.4 Repeat Steps 3a-3e until the desired number of features is selected or a stopping criterion is met for each group.

The application of MRMR in rice recognition using machine learning techniques can result in increased classification accuracy and efficiency. By selecting the most pertinent features, the algorithm reduces dimensionality and improves classification model performance.

2.3 Training the Proposed Model Using ML Classifiers

This study proposes an ML-RVR framework that employs a comprehensive analysis of the dataset using six distinct machine learning classifiers. These classifiers consist of Decision Trees, K-Nearest Neighbors, Support Vector Machines, Ensemble methods, Neural Networks, and Gaussian Nave Bayes. The proposed Algorithm 2 with employed classifier is presented here.

Algorithm2 : Machine Learning-based Rice Variety Recognizer
Input: Rice dataset, Machine Learning Classifiers
Output: ML-RVR framework classification results for rice variety recognition.

Step.1 Begin
Step.2 Ensure a suitable ratio for model evaluation by dividing the preprocessed dataset into training and test sets.
Step.3 Initialize an empty list to store each classifier's classification results.
Step.4 For each classifier in the set based on machine learning:
a) Train the classifier on the training dataset using the algorithm for the specific classifier.
b) Evaluate the trained classifier using the testing dataset to determine classification accuracy and other performance metrics.
c) Record the classification results.
Step.5 Repeat steps 4a to 4c for each type of classifier in the ML-RVR framework, including Decision Trees, KNN, SVM, Ensemble methods, Neural Networks, and Gaussian Naïve Bayes.
Step.6 Compare the performance of each classifier by analyzing the classification results obtained in step 4. Identify the classifiers that yield the highest accuracy or best performance metrics for rice variety recognition.
Step.7 Based on the evaluation, identify top-performing classifiers for rice variety recognition for proposed model.
Step.8 End

The proposed model obtains the high accuracy with Ensemble ML and Neural Network classifiers. These classifiers accurately classify the rice varieties in the dataset, demonstrating their efficacy. XGBoost optimizes the ensemble of weak learners through gradient boosting, enhancing predictive accuracy by iteratively refining the model based on the shortcomings of preceding weak models. Neural Networks are potent models capable of discovering intricate data patterns and relationships. These classifiers provide valuable insights into the dataset, enabling the accurate classification of rice varieties based on their unique characteristics.

3 Experimental Results and Analysis

The experimental results demonstrate the efficacy and performance of the ML-RVR rice variety recognition framework. The 106-attribute rice dataset was utilized to evaluate the classifiers, which included DT, KNN, SVM, Ensemble methods, Neural Networks, and Gaussian Nave Bayes. The detailed findings are presented here.

The proposed ML-RVR generated the confusion matrix to evaluate the performance of machine learning classification algorithms. This matrix gives useful information about the relationship between classifier performance and test outcomes. It can distinguish between proper and erroneous positive and negative sample classifications. The rows correspond to the actual class labels, while the columns represent the predicted class labels. The generated confusion matrix shown in Table 2 presents the classification system's accuracy in accurately recognizing distinct classes.

Table 2. Evaluating Model Performance through Confusion Matrix Analysis

Rice Type	Algorithm	Arborio	Basmati	Ipsala	Jasmine	Karacadag
Arborio	DT	13390	0	2	38	70
	KNN	13449	0	1	38	12
	SVM	13479	0	0	16	5
	Ensemble	13467	0	0	22	11
	NN	13475	0	0	19	6
	Naive byes	13330	0	0	76	94
Basmati	DT	0	13403	2	95	0
	KNN	1	13470	0	29	0
	SVM	0	13487	0	13	0
	Ensemble	0	13457	0	43	0
	NN	0	13482	1	17	0
	Naive byes	0	13278	0	222	0
Ipsala	DT	43	3	13444	10	0
	KNN	7	0	13493	0	0
	SVM	5	1	13494	0	0
	Ensemble	9	1	13489	1	0
	NN	5	0	13495	0	0
	Naive byes	3	0	13484	13	0
Jasmine	DT	37	24	5	13429	5
	KNN	36	9	1	13451	3
	SVM	10	2	0	13488	0
	Ensemble	21	10	1	13467	1
	NN	30	11	0	13459	0
	Naive byes	36	13	3	13447	1
Karacadag	DT	74	0	1	0	13425
	KNN	45	0	0	0	13455
	SVM	10	0	0	0	13490
	Ensemble	27	0	0	1	13472
	NN	17	0	1	1	13481
	Naive byes	54	0	0	0	13446

Following that, the ML-RVR framework uses all of the classifier methods to the 106-attributes dataset at a training rate of 90%. To measure the performance of the models, the evaluation metrics precision, recall, and F1 score were generated. The outcomes of these measures are shown below. The results in Table 3 indicate that the variants of the neural network achieved effective training compared to the other classifiers.

Table 3. Results of Classifiers on all Attributes

CLASSIFIERS	ALGORITHM	PRECISION	RECALL	F1 SCORE
DT	FINE	0.9968	0.9968	0.9961
	MEDIUM	0.9942	0.9944	0.9942
	COARSE	0.8585	0.7864	0.7318
KNN	FINE	0.9976	0.9976	0.9976
	MEDIUM	0.9968	0.9968	0.9968
	COARSE	0.9956	0.9954	0.9954
	CUBIC	0.9974	0.9974	0.9974
	COSINE	0.9972	0.9974	0.9972
	WEIGHTED	0.9974	0.9974	0.9974
SVM	LINEAR	0.9984	0.9982	0.9982
	CUBIC	0.9994	0.9992	0.9992
	QUADRATIC	0.9992	0.9992	0.9992
	FINE GAUSSIAN	0.7836	0.9826	0.8718
	MEDIUM GAUSSIAN	0.9999	0.9999	0.9999
	COARSE GAUSSIAN	0.9987	0.9987	0.9987
ENSEMBLE	BOOSTED	0.9978	0.9981	0.9978
	BAGGED	0.9981	0.9984	0.9989
	SUBSPACE KNN	0.9122	0.9128	0.9124
	SUBSPACE DISCRIMINANT	0.9954	0.9952	0.9952
	RUSBOOSTED TREE	0.9942	0.9964	0.9952
NN	NARROW	0.9988	0.9988	0.9988
	MEDIUM	0.9982	0.9984	0.9982
	WIDE	0.9988	0.9984	0.9985
	BILAYERED	0.9992	0.9992	0.9992
	TRILAYERED	0.9982	0.9982	0.9982
NAIVE BAYES	GAUSSIAN NAIVE BAYES	0.9914	0.9912	0.9912

Figure 6 depicts the validation and test accuracy of different classifiers and their versions. It is noteworthy that the Fine version of Decision Trees and KNN exhibit superior performance in comparison to their medium and coarse counterparts. The utilization of the Cubic variant of SVM has been observed to demonstrate enhanced precision in accurately capturing nonlinear associations. The ensemble approach's Boosted version exhibits improved performance through the amalgamation of feeble classifiers. The empirical evidence suggests that Wide Neural Networks exhibit superior accuracy in comparison to their narrow and medium counterparts. Additionally, Gaussian Naïve

Bayes demonstrates competitive performance in this context. The graph provides a clear illustration of the superior performance of these particular versions, emphasizing their accuracy in categorizing the rice dataset.

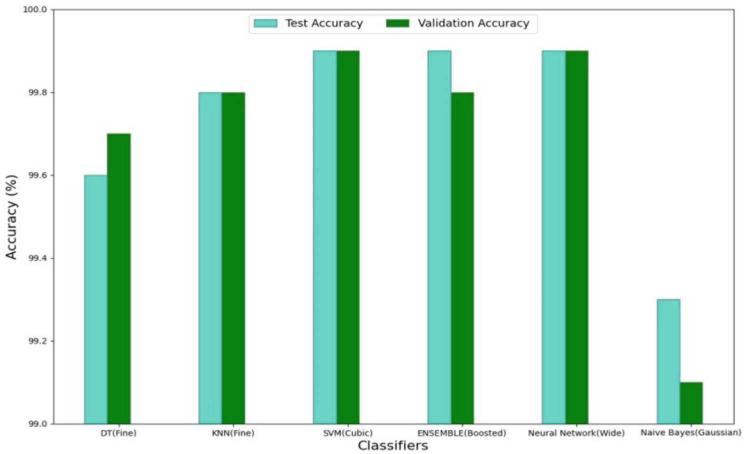

Fig. 6. Accuracy of Classifiers

The experimental study continued to investigate the impact of attribute selection ranking algorithm and analyzed the dataset using the top 90 ranking features, followed by the top 80 and top 70. The corresponding accuracies for each feature subset are presented in Table 4. Based on the results, it was observed that the MRMR algorithm effectively ranked the attributes for classifying the dataset. It was found that using a minimum of 70 attributes resulted in the highest accuracy, surpassing the consideration of all attributes. This finding is significant as it not only improves the classification performance but also reduces the space and time complexities associated with the proposed work.

This study investigates the impact of MRMR utilizing the highest-ranked attributes (70, 80, and 90) out of a total of 106 attributes on the efficacy of the optimal classifiers. Empirical evidence shown in Fig. 7 indicates the utilization of at least 70 attributes produces optimal outcomes that are comparable to those obtained by employing the complete set of attributes.

Feature engineering is conducted on the outperforming Neural Network (NN) classifier using MRMR, ANOVA, Kruskal Wallis, Information Gain, and Chi2, as illustrated in Fig. 8. The results indicate that MRMR outperforms the other feature selection methods. The aforementioned discovery underscores the effectiveness of utilizing MRMR for feature selection in order to decrease the dataset's dimensionality, all the while preserving the classification accuracy of the classifiers. The reduction of computational complexity and resource requirements of classifiers can be achieved without compromising performance by taking into account the most highly ranked attributes.

Table 4. Results of ML Classifiers with Feature Engineering

Classifiers (MRMR)	Algorithm	(90/106)		(80/106)		(70/106)	
		Valida-tion %	Test %	Valida-tion %	Test %	Valida-tion %	Test %
DT	Fine	99.6	99.7	99.6	99.7	99.6	99.6
	Medium	99.4	99.4	99.4	99.4	99.4	99.4
	Coarse	78.6	78.6	78.6	78.6	78.5	78.5
KNN	Fine	99.8	99.8	99.8	99.8	99.8	99.8
	Medium	99.8	99.8	99.8	99.8	99.8	99.8
	Coarse	99.6	99.7	99.7	99.7	99.7	99.8
	Cubic	99.7	99.7	99.7	99.8	99.7	99.8
	Cosine	99.8	99.8	99.8	99.8	99.8	99.8
	Weighted	99.8	99.8	99.8	99.8	99.8	99.8
SVM	Linear	99.8	99.8	99.8	99.9	99.8	99.8
	Cubic	99.9	99.9	99.9	99.9	99.9	99.9
	Quadratic	99.9	99.9	99.9	99.9	99.9	99.9
	Fine Gaussian	98.5	98.5	98.7	99.9	99	99.2
	Medium Gaussian	99.9	99.9	99.9	99.9	99.9	99.9
	Coarse Gaussian	99.8	99.8	99.8	99.8	99.8	99.8
Ensemble	Boosted	99.8	99.8	99.8	99.8	99.8	99.8
	Bagged	99.7	99.7	99.7	99.8	99.8	99.8
	Subspace KNN	91.2	90.8	91	90.8	90.1	89.7
	Subspace Discriminant	99.6	99.5	99.6	99.5	99.6	99.4
	Rusboosted Tree	99.4	99.4	99.4	99.4	99.4	99.4
Neural Network	Narrow	99.8	99.9	99.8	99.9	99.8	99.9
	Medium	99.9	99.9	99.9	99.9	99.9	99.9
	Wide	99.9	99.9	99.9	99.9	99.9	99.9
	Bilayered	99.8	99.9	99.8	99.9	99.8	99.9
	Trilayered	99.8	99.9	99.8	99.9	99.8	99.8
Naive Bayes	Gaussian Naive Bayes	99.2	99.2	99.3	99.3	99.3	99.3

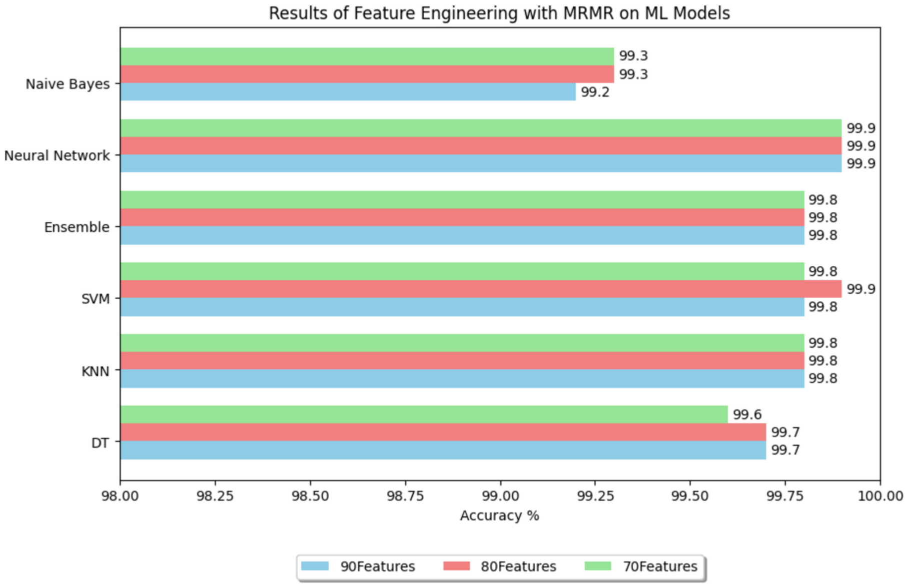

Fig. 7. Performance of MRMR on ML Classifiers

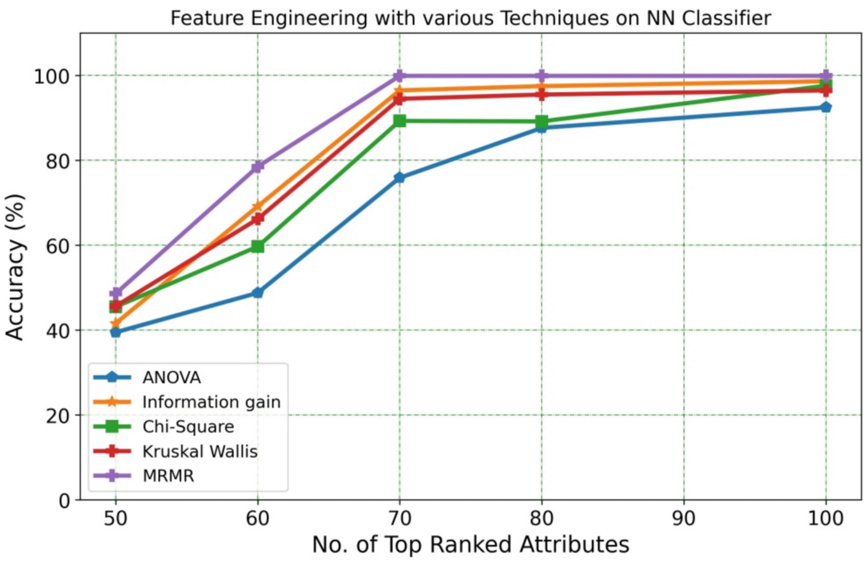

Fig. 8. Results of Feature Engineering on NN Classifier

4 Conclusion

In conclusion, rice plays a crucial role as an essential meal worldwide and is of the utmost economic and nutritional significance in our country. Using machine learning techniques, this study aimed to develop a classification framework for rice varieties. The study analyzed a dataset containing 106 features, and the classification procedure was carried out by identifying the most significant attributes using the proposed framework. The application of the Maximum Relevance Minimum Redundancy (MRMR) attribute selection method was effective in identifying the most vital characteristics of the dataset. The evaluation of various machine learning classifiers, such as Neural Networks, SVM, and KNN, demonstrated their accuracy in rice classification. These classifiers were able to accommodate the diverse characteristics of rice samples and produce accurate classification results.

The results of this study have important implications for rice producers, researchers, and policymakers in terms of enhanced rice variety recognition and a better understanding of the diverse characteristics associated with distinct rice types. This framework facilitates informed decision-making processes regarding rice production, resource allocation, and food security, ultimately resulting in improved agricultural practises and outcomes. As rice remains an essential crop, intelligent frameworks for rice variety recognition contribute to sustainable agriculture and food production.

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