Journal of Social Work and Science Education
Volume 7 (1) 2026, 522-540
E-ISSN 2723-6919, P-ISSN 2746-0827

Recognition and Prediction of Rice Variety–Climate Suitability Using YOLOv9 and Naïve Bayes in Agricultural Lands

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Article History: Received on 2 December 2025, Revised on 1 January 2026, Published on 2 February 2026

Abstract: The suitability of rice varieties to agroclimatic conditions is a key factor in determining rice productivity in Indonesia. Climate variability and land limitations require a decision support system capable of assisting farmers in selecting rice varieties suitable for local environmental conditions. This study aims to develop an integrated artificial intelligence-based system that combines YOLOv9 for image-based rice variety recognition and Naïve Bayes for climate suitability prediction based on temperature and humidity parameters. Image data of five rice varieties Ciherang, Inpari 32, Inpari Nutrizinc, Mekongga, and Baroma were collected directly from agricultural fields in Bandung Regency and processed through annotation, augmentation, and model training stages. The YOLOv9 model performed well in distinguishing rice varieties with relatively similar morphological characteristics, with an mAP@50 value of 0.8932. Meanwhile, the Naïve Bayes model achieved 78% accuracy in predicting climate suitability based on altitude, temperature, and humidity, and produced predictions consistent with agronomic recommendations. Both models were then integrated into a Gradio-based interactive interface to facilitate use by non-technical users. The results indicate that this integrated approach has the potential to be an effective decision support system for assisting in the selection of rice varieties that are adaptive to microclimate conditions, thereby supporting more efficient and sustainable rice cultivation practices.

Keywords: Agricultural Decision Support, Climate Suitability, Naïve Bayes, Rice Varieties, Using YOLOv9

A. Introduction

Rice is a strategic food commodity that has a fundamental role in maintaining Indonesia's national food security. The high level of rice consumption makes stable rice production a key factor for economic, social, and political sustainability (Badgujar et al., 2024; Z. Li et al., 2025). However, rice productivity in various regions, including Bandung Regency, still faces significant challenges due to climate variability, land conversion, and the inaccuracy of selecting varieties suited to local agro-climatic conditions.

Various agronomic studies show that successful rice cultivation is greatly influenced by the compatibility of varietal characteristics with environmental factors such as temperature (Sperandio et al., 2025), humidity (Sathiyamurthi et al., 2024), and altitude (Agrawal et al., 2025). Each rice variety has different physiological thresholds for climate and topographic conditions. A mismatch between variety and growing environment often leads to decreased yields, increased risk of pest and disease attacks, and inefficient use of agricultural inputs. In practice, farmers still rely heavily on empirical experience or general recommendations that do not fully consider microclimatic variations between regions, thus preventing optimal yield potential.

The development of artificial intelligence (AI) technology is opening up new opportunities to support decision-making in the agricultural sector (Lu et al., 2024). One rapidly developing branch of AI is computer vision, which enables systems to automatically recognize and classify visual objects. Deep learning-based object detection models, particularly You Only Look Once (YOLO), have been widely applied in agricultural contexts, such as plant disease detection (P. Li et al., 2025; Qin et al., 2025), grain quality identification, and rice variety classification (Shahriar Zaman Abid et al., 2024; Wang et al., 2025). YOLOv9, the latest version, presents improvements to the network architecture and feature extraction mechanism, enabling it to distinguish objects with subtle morphological differences while remaining reliable under varying lighting and background conditions in the field (Gao et al., 2024; Pan et al., 2025) .

On the other hand, climate suitability analysis requires a classification approach that can utilize numerical data such as temperature, humidity, and altitude (Zhang et al., 2024). The Naïve Bayes method is one of the algorithms widely used in agriculture due to its simplicity, computational efficiency, and ability to produce easily interpretable models. Although the assumption of independence between features is an inherent limitation of this method, Naïve Bayes has proven effective in various climate-based prediction studies and agronomic decision-making, especially under conditions of limited data availability.

Although previous research has discussed the application of YOLO for visual plant recognition and the use of Naïve Bayes for land or climate suitability analysis (Miao et al., 2025), the integration of these two approaches into a single, comprehensive decision support system is still relatively limited (Shams et al., 2024; Wen et al., 2025). In particular, there are few studies that combine field image-based rice variety recognition with probabilistic climate suitability prediction to support variety selection that is adaptive to local environmental conditions.

Based on these research shortcomings, this study proposes an integrated framework that combines YOLOv9 for rice variety recognition and Naïve Bayes for climate suitability prediction based on temperature and humidity parameters. This system was developed using image data collected directly in the field and specific agroclimate data for the Bandung Regency region. By integrating visual recognition and climate suitability analysis into a single workflow, this research is expected to contribute to the development of a more adaptive, accurate, and applicable AI-based decision support system to support sustainable rice cultivation practices.

B. Methods

Data Collection

Primary image acquisition was conducted across agricultural zones in Bandung Regency, capturing representative samples of five rice varieties. The collected images reflect real field conditions variations in lighting, angles, and growth stages thereby increasing ecological validity. Climatic data, especially temperature and relative humidity, were obtained through a combination of field measurements and region-specific agronomic (Islam et al., 2026).

All images were annotated manually using bounding boxes. Data augmentation was applied extensively to address dataset limitations and improve model generalization. Augmentation included rotational transformation, horizontal and vertical flipping, zoom adjustments, and controlled brightness contrast manipulation (Koklu et al., 2021). The dataset was subsequently partitioned into training, validation, and test sets following standard machine-learning practices.

YOLOv9 Model Training

Model training adhered to the canonical YOLOv9 pipeline, which utilizes an ELAN-based backbone for hierarchical feature extraction, a PANet-like structure for multi-scale feature fusion, and a multi-branch detection head for bounding-box prediction (Shams et al., 2024). Model performance was evaluated using precision, recall, and mean average precision (mAP) metrics at multiple IoU thresholds.

Naïve Bayes Suitability Classification

The Naïve Bayes classifier was implemented to categorize climate suitability using temperature and humidity as predictor variables. Suitability labels were derived from established agronomic guidelines. The probability model employed Bayes' theorem:

$$P(Y|X) = \frac{P(X|Y)P(Y)}{P(X)} \qquad (1)$$

Evaluation was conducted using accuracy metrics and confusion matrices for both elevation-based and climate-based suitability schemes.

System Integration and Interface Development

To enhance usability, both models were embedded within an interactive Gradio interface. The interface allows users to upload rice plant images, obtain varietal recognition, and receive corresponding climate suitability assessments, enabling intuitive access for non-technical stakeholders.

C. Results and Discussion

The data collection process was conducted through direct fieldwork facilitated by the Bandung Regency Agriculture Office. The researcher visited BPP Bojongsoang, collecting rice-plant images from several field locations, including Cibojong, Haur Hapit, and Bojongsari. This field survey produced 150 images representing three varieties: Ciherang (50 images), Inpari Nutrizinc (50), and Inpari 32 (50).

To complement the dataset, two additional varieties Baroma and Mekongga were sourced from YouTube by extracting screenshots, adding 100 images (50 per variety). The final dataset therefore comprised 250 rice-plant images across five varieties.

In addition to visual data, the researcher collected variety description documents (2023 edition) provided by the Agriculture Office and retrieved climate data for Bandung Regency from the local BPS website. These materials were compiled into a single repository for use in model training and evaluation.

Temperature and humidity tolerance data for each variety were obtained from scientific literature (Table 1) and cross-referenced with elevation-based suitability information extracted from official variety descriptions (Table 2). Climatic attributes were then integrated with varietal characteristics as summarized in Table 3.

Table 1. Temperature and Humidity Based on Altitude

Altitude (MDPL)	Average Air Temperature (Max)	Average Air Temperature (Min)	Average Air Temperature (Daily)	Humidity
50	33.3	24	27.5	82.2
368	30.5	21.2	25.3	84
693	28.6	18.8	24.4	85.5
865	27.3	18.2	23.1	86.7

Source: Listia, et.al (2019)

Table 1 shows the relationship between altitude (masl) and key climate parameters, namely air temperature and relative humidity. The data show a consistent altitudinal gradient pattern, where increasing altitude is inversely proportional to air temperature and directly proportional to humidity. At low altitudes (50 masl), the maximum temperature recorded was highest, at 33.3°C, with a daily average temperature of 27.5°C and a relative humidity of 82.2%. As altitude increases to 865 masl, the maximum and minimum temperatures decrease significantly, to 27.3°C and 18.2°C, respectively, while the daily average temperature drops to 23.1°C. Conversely, relative humidity increases to 86.7%. This study confirms that altitude is a major determinant of microclimate variation, which directly influences the suitability of the growing environment for certain rice varieties. Therefore, altitude can be used as an early indicator to predict the temperature and humidity ranges that rice plants will encounter.

Table 2. Rice Variety Suggest

Variety	Min Latitude	Max Latitude
Inpari 32	0	600
Inpari Nutri Zinc	0	600
Mekongga	0	500
Baroma	0	600
Ciherang	0	500

Source: BSIP (2023)

Table 2 shows the recommended minimum and maximum altitude limits for five rice varieties: Inpari 32, Inpari Nutri Zinc, Mekongga, Baroma, and Ciherang. These data indicate that not all varieties have the same altitude tolerance. Inpari 32, Inpari Nutri Zinc, and Baroma are recommended for areas with an altitude of 0–600 meters above sea level, reflecting their relatively broad adaptability to lowland to midland conditions. In contrast, Mekongga and Ciherang have a lower maximum altitude limit, at 0–500 meters above sea level, making them more suitable for planting in lowland to lower-middleland areas. The results of this study indicate that selecting varieties that are not suited to land altitude has the potential to cause climate mismatches, particularly related to air temperature decreasing with increasing altitude.

Table 3. Varieties Integrated with Temperature and Humidity

Variety	Min Lat	Max Lat	Min Temp	Max Temp	Avg Temp	Hum
Inpari 32	0	600	18.8	28.6	24.4	85.5
Inpari Nutri Zinc	0	600	18.8	28.6	24.4	85.5
Mekongga	0	500	21.2	30,5	25.3	84
Baroma	0	600	18.8	28.6	24.4	85.5
Ciherang	0	500	21.2	30.5	25.3	84

Table 3 shows the integration of variety altitude data (Table 2) with temperature and humidity characteristics based on altitude (Table 1). This integration yields a specific climate tolerance range for each variety, which is then used as the basis for determining climate suitability labels in Naive Bayes modeling. The Inpari 32, Inpari Nutri Zinc, and Baroma varieties have a minimum temperature range of 18.8°C, a maximum temperature of 28.6°C, an average temperature of 24.4°C, and a relative humidity of 85.5%. These characteristics indicate that these three varieties are more suited to areas with relatively cool climates and high humidity, which are generally found at mid-altitudes. Meanwhile, the Mekongga and Ciherang varieties exhibit higher temperature tolerance, with a maximum temperature reaching 30.5°C and an average daily temperature of 25.3°C, and a slightly lower relative humidity of 84%. This indicates that these two varieties are more adaptable to lowland conditions, which tend to be hotter.

Data pre-Processing

Pre-processing was performed using three primary datasets desk.csv, iklim.csv, and ketinggian.csv to prepare the numerical inputs for Naïve Bayes classification as follows (1) Data cleaning with column names were standardized for uniformity, Non-numeric values and missing entries were removed or coerced into numeric format, this step ensured compatibility with downstream computation and prevented parsing errors. (2) Dataset construction with the three datasets were merged to generate all Variety × Subdistrict × Month combinations, suitability labels (Cocok, Kurang Cocok, Tidak Cocok) were assigned based on varietal requirements, label generation used: Elevation thresholds from varietal description tables (Tabel 2), Temperature ranges from literature-based varietal tolerance values (Tabel 1) and Monthly humidity averages (Tabel 3). (3) Feature selection with numerical features: elevation, min temperature, max temperature, humidity, target variables: elevation label and climate label. (4) Feature scaling with standardization was applied using *StandardScaler* on the training subset only to avoid data leakage. (4) Train–Test Split with Stratified partitioning was applied with 80% training and 20% testing, ensuring balanced suitability labels.

Data Labeling

All rice-plant images were manually annotated in Roboflow prior to YOLOv9 training. Each image received as follows (1) A class label corresponding to one of the five rice varieties: Ciherang, Inpari 32, Inpari Nutrizinc, Mekongga, Baroma and (2) Bounding boxes adjusted to the plant's position within the image. Labeling results are illustrated in figure 1 and figure 2.

Journal of Social Work and Science Education
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E-ISSN 2723-6919, P-ISSN 2746-0827

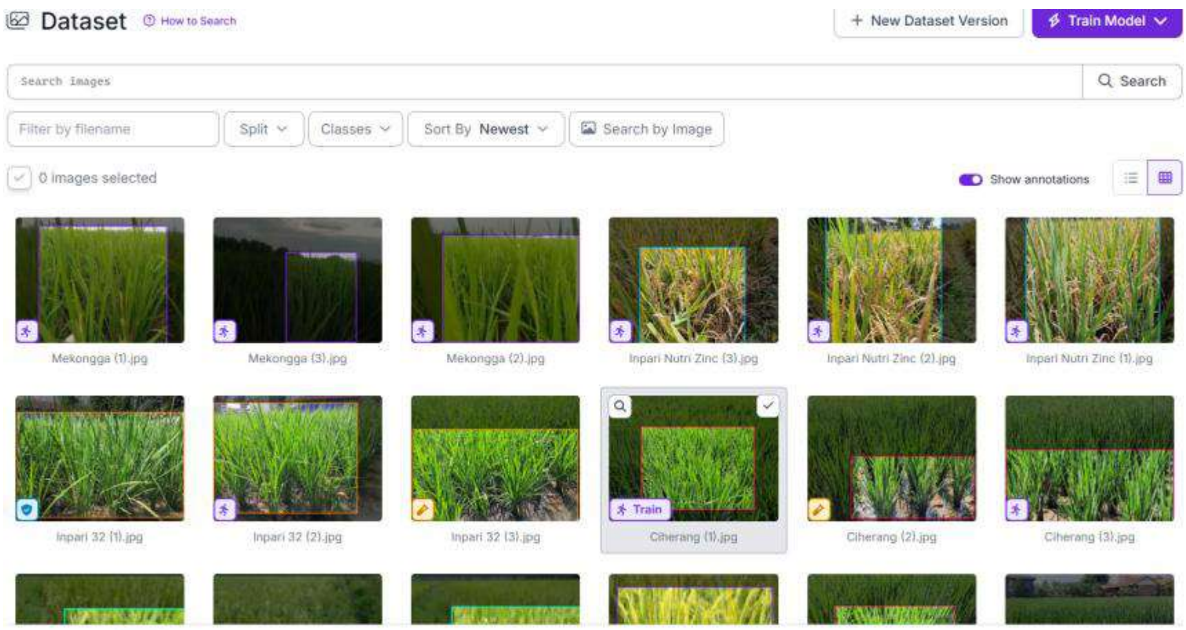

Figure 1. Example of Bounding Box Labeling

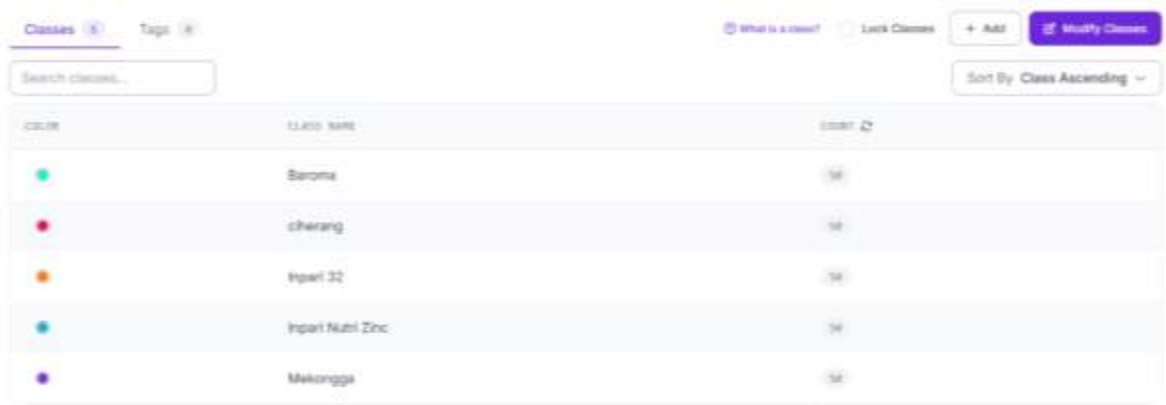

Figure 2. Label Distribution in Dataset

These figures show both the bounding-box annotation workflow and proportional distribution of class labels.

Data Augmentation

Using Roboflow, the 250 manually labeled images were augmented to produce **650 images** via as follows (1) Horizontal & vertical flips 90° rotations (clockwise, counterclockwise, upside down). (2) Cropping (0–25% zoom). (3) Random rotations (–15° to +15°). (4) Brightness adjustments (–15% to +15%).

Dataset Splitting

The expanded dataset of 650 images was split into as follows (1) 80% Training set (600 images) (2) 10% Validation set (25 images) (3) 10% Test set (25 images). This partition ensures robust training, hyperparameter tuning, and unbiased model evaluation.

Recognition Model Training

The model training stage is a crucial step in the object detection process for rice varieties. In this stage, the model learns to recognize and classify objects (rice varieties) from previously prepared training data. This training process is carried out using the YOLOv9 model architecture managed by the Ultralytics framework. The model used is YOLOv9c.pt, a pre-trained model with a compact architecture. This pre-trained model implements the concept of transfer learning, where the weights of a model trained on a common dataset (such as ImageNet) are adjusted to recognize specific objects (rice varieties) in a new dataset. This approach allows the model to achieve optimal performance even with a relatively small amount of training data.
During the training process, several key parameters are configured to optimize model performance. These parameters are:

a. Dataset: The training dataset is defined in the data.yaml configuration file, which contains information about the annotations and a list of rice variety classes to be detected.
b. Epochs: The model was trained for 100 epochs. One epoch represents one cycle in which the model has traversed the entire training dataset. This number of epochs was chosen to ensure the model has sufficient opportunity to learn from the data without overfitting.
c. Image Size: The input image size used for training is 640x640 pixels. This is a standard resolution that provides a balance between sufficient visual detail for detection and computational efficiency.

After the training process is complete, the trained model is automatically saved with the file name yolov9_rice_detection.pt. This model has been adjusted to detect the rice varieties in the dataset. The training results, including performance metrics such as loss and accuracy, can be further analyzed to evaluate the model’s ability to detect rice varieties. This model will then be used for testing and inference on new data.

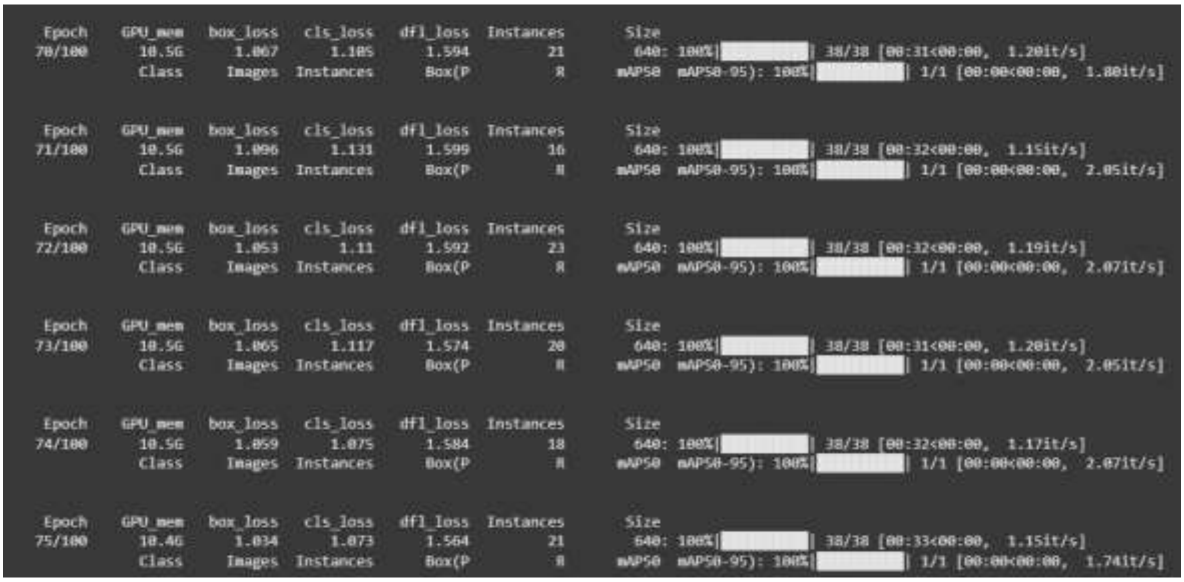

Figure 3. Image Data Training Process

After 100 epochs of training, the YOLOv9c model was successfully trained to detect the specified rice varieties. The training process took approximately 0.970 hours. The results of this training were evaluated to measure the model's performance in detecting and identifying rice varieties in the validation dataset. The best model from the training results, saved as best.pt, had the YOLOv9c architecture with a total of 25,323,103 parameters.

Recognition Model Testing

The model testing phase is the final evaluation to measure the trained model's ability to detect and identify objects in previously unseen datasets. The goal of this testing is to independently validate the model's performance and ensure that the model has good generalization capabilities.

Model testing is conducted using a test dataset separate from the training and validation datasets. This dataset consists of a collection of labeled images of rice varieties that have never been used in the training process. The model tested is the best model resulting from the training process, yolov9_rice_detection.pt (or best.pt), which has been optimized for 100 epochs.

The following are the testing steps the researchers followed.
1. Testing begins by loading the pre-trained model.
2. Detect the image data called by the trained YOLOv9 model.
This model will analyze the image to identify the called rice variety and return the variety name (e.g., 'Ciherang' or 'Inpari 32') with a bounding box.

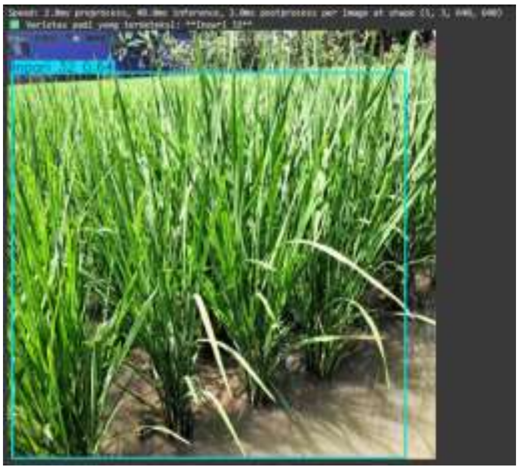

Figure 4. Detected Rice Image

The image above shows that the model detected the 'Inpari 32' variety.

Table 4. Recognition Model Test Results

Class	Images	Instances	Box (P)	R	mAP50	mAP5095
all	25	25	0.767	0.809	0.893	0.424
Baroma	4	4	0.536	0.750	0.828	0.366
Inpari32	6	6	0.909	1.000	0.995	0.515
Inpari Nutri Zinc	4	4	0.705	0.615	0.745	0.296
Mekongga	6	6	0.803	0.680	0.903	0.412
Ciherang	6	5	0.880	1.000	0.995	0.529

The test results show that the model has a good overall mAP50 (mean average precision) value. mAP50 is the model's ability to determine locations (bounding boxes) and predict the image's characteristics. The threshold value for mAP50 is 0.50, or 50%. However, at mAP50-95.

Recognition Model Evaluation

After the recognition model training process is complete, an evaluation is conducted to objectively measure the model's performance. This stage uses a separate validation dataset to ensure the model can reliably detect objects on previously unseen data. The results of this evaluation serve as a key indicator of the model's success in the rice variety detection task.

The model evaluation process is performed automatically by the Ultralytics framework after training is complete. The validation dataset consists of 25 images, each containing annotations for rice varieties. The evaluation metrics used include Precision (P), Recall ®, and Mean Average Precision (mAP) at an Intersection over Union (IoU) threshold of 50% (mAP50) and a range of 50-95% (mAP50-95).

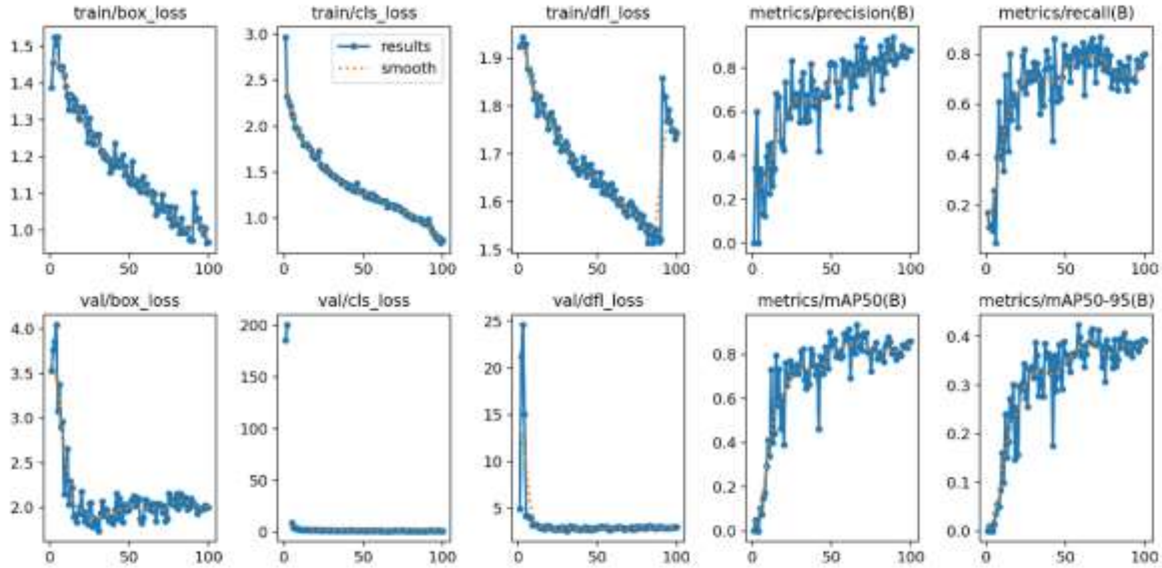

Figure 5. Results Graph

The figure above displays a graph of the YOLOv9c model training evaluation over 100 epochs, including key metrics such as loss, precision, recall, and mean average precision (mAP). The graph above shows that the loss for all three training sessions decreased until completion, although the box loss and DFL loss increased for a short time. This indicates that the model successfully learned to recognize objects better as the number of epochs increased. Furthermore, during the validation process, the graph shows a gradual decrease in loss. This proves that the model did not experience overfitting and maintained good performance on new data not yet used during training.

Overall, the decreasing loss trend remained consistent, and model performance, measured using evaluation metrics such as mAP, showed stable results. Therefore, although there was a temporary increase in DFL Loss at the end of training, this does not indicate a failure of the training process but is rather part of the normal dynamics of the object detection model optimization process.

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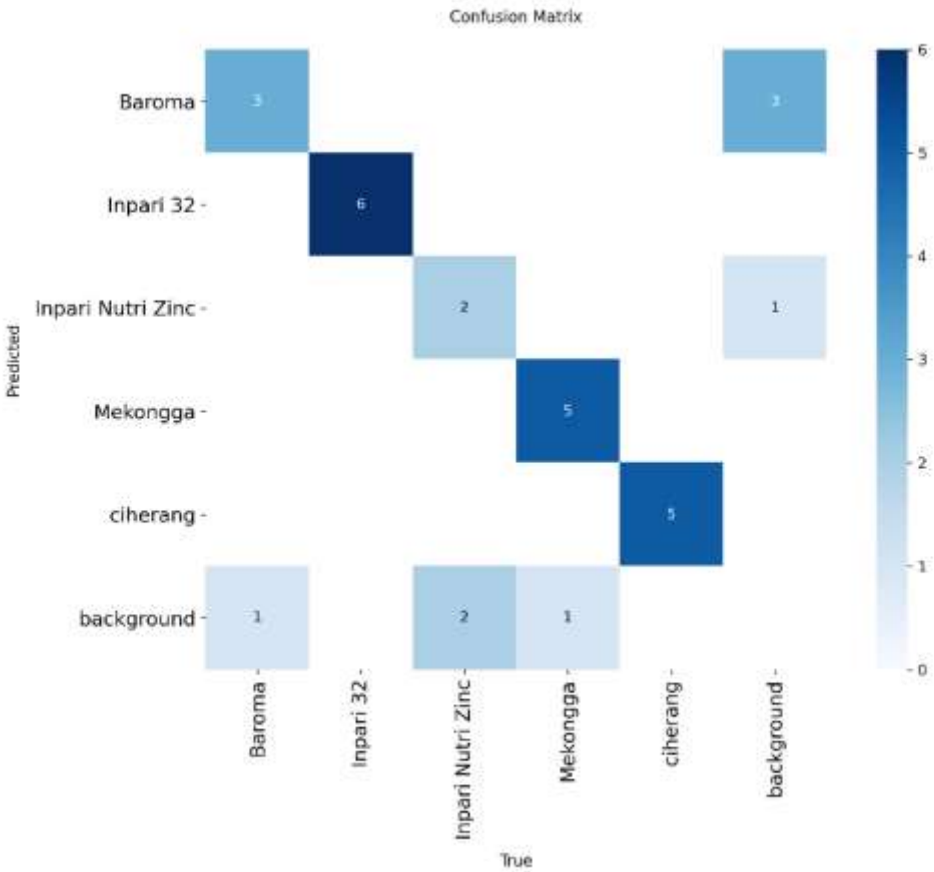

Figure 6. Confusion Matrix

Figure 6 shows that the YOLO model was able to detect the Baroma, Inpari 32, Ciherang, and Mekongga rice varieties with perfect accuracy (100%). However, there was a detection error for the Inpari Nutri Zinc variety, with one image classified as background. Furthermore, errors occurred quite frequently in the background class, where some blank images were detected as specific varieties. This indicates that the model still has limitations in distinguishing background images from variety objects. However, for rice varieties with clear, stronger visual characteristics, detection performed very well.

The overall model evaluation metrics are as follows:

a. mAP50: 0.8932
b. mAP50-95: 0.4238
c. Precision: 0.7664
d. Recall: 0.8092

Based on the evaluation results, the YOLO model demonstrated quite good performance and accuracy. The mAP50 value of 0.8932 indicates that at an IoU threshold of 0.5, the model was able to detect objects with a high degree of accuracy. However, in a more stringent evaluation using mAP50-95, the value obtained was

0.4238, indicating that model performance decreased when bounding box accuracy was required to be more precise.

Furthermore, a precision value of 0.7664 indicates that approximately 76.64% of the model's detections were correct (minimal detection errors). Meanwhile, a recall of 0.8092 indicates that the model successfully detected approximately 80.92% of all objects. Overall, this model is quite effective at detecting objects, although there is still room for improvement in detection consistency across IoU variations.

Prediction Model Training

After the evaluation stage of the recognition model is complete, the next step is training the prediction model. The model used in this study is Naïve Bayes, chosen for its simplicity, computational speed, and ability to handle small to medium-scale data well. At this stage, the preprocessed dataset is divided into two parts: 80% training data and 20% testing data. The training data is used to build the model by learning the relationship between input features (altitude, minimum temperature, maximum temperature, and humidity) and the output labels, namely Label_Ketinggian and Label_Iklim. Meanwhile, the testing data is used to measure the performance of the trained model.

Training is conducted separately for both labels. For the first label (Label_Ketinggian), the model learns to determine suitability categories based on the variety's altitude tolerance to the land. For the second label (Label_Iklim), the model learns the variety's suitability to monthly climate conditions based on predetermined temperature and humidity ranges.

To ensure the reliability of the results, the training process also implemented a stratified split, ensuring that the class distribution in the training and test data remained balanced. This allowed the model to learn from proportional representation for each class.

Prediction Model Testing

Prediction model testing was conducted after the training process was completed to determine the model's ability to predict previously unseen data. The test data used represented 20%, or 372, of the total 1,860 datasets that had undergone preprocessing. This data was separated from the training data using a train-test split method, ensuring complete independence from the training data.

In the testing phase, the trained prediction model received input in the form of numeric features: altitude (masl), minimum temperature, maximum temperature, and average humidity. Based on these features, the model provided class predictions for two labels: label ketinggian (Cocok, Kurang Cocok, Tidak Cocok) and label iklim (Cocok, Tidak Cocok). After testing, the model performed well, with an accuracy of 0.78, or 78%, in predicting the suitability of varieties for agricultural climates.

Prediction Model Evaluation

In this stage, the Naive Bayes model is evaluated on the test data, previously separated from the training data. This evaluation uses precision, recall, f1-score, and accuracy metrics, which are displayed in a classification report and visualized with a confusion matrix.

Table 5. Naive Bayes Evaluation Label_Ketinggian

	Precession	Recall	F1-Score	Support
Less Suitable	0.58	1.00	0.73	115
Not Suitable	1.00	0.68	0.81	257
Accuracy			0.78	372
Macro Avg	0.79	0.84	0.77	372
Weight Avg	0.87	0.78	0.78	372

Table 6. Naive Bayes Evaluation Label_Iklim

	Precession	Recall	F1-Score	Support
Cocok	1.00	1.00	1.00	372
Accuracy			1.00	372
Macro Avg	1.00	1.00	1.00	372
Weight Avg	1.00	1.00	1.00	372

Based on the evaluation results table for the “Height Label,” the model successfully predicted the suitability of rice varieties for the agricultural climate. This is evidenced by the model achieving an accuracy of 78%. The “Kurang Cocok (unsuitable)” class had perfect recall (100%) but relatively low precision (58%), indicating that the model frequently predicted data as Kurang Cocok (less suitable) even though some were actually Tidak Cocok (Unsuitable). Conversely, the “Tidak Cocok” class achieved perfect precision (100%) but lower recall (68%), indicating that some Unsuitable data were still misclassified. Overall, the f1-score for the Kurang Cocok class was 0.73, while for the Unsuitable class it was 0.8.

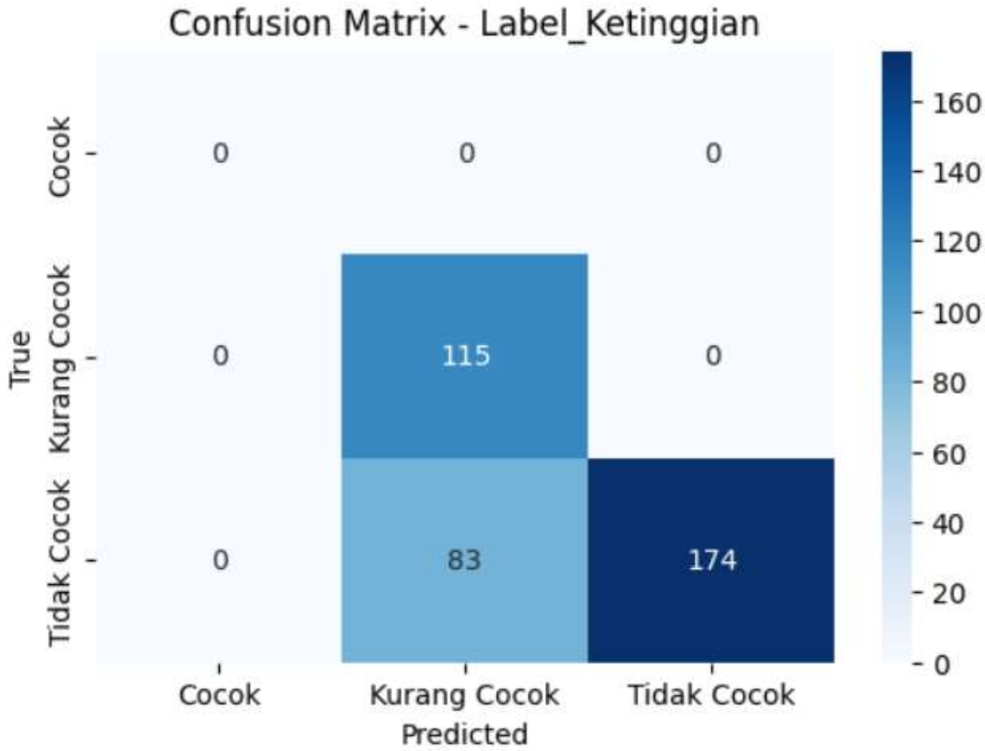

Figure 7. Confusion Matrix Label_Height

Figure 7 shows that 115 actual data points predicted as "Kurang Cocok" were correctly predicted. Of the 257 actual data points predicted as "Tidak Cocok," 174 were correctly predicted, and 83 were incorrectly predicted as "Kurang Cocok." Figure 4.8 shows that 372 actual data values are labeled "Cocok." There are no data labeled "Kurang Cocok" or "Tidak Cocok" in the test dataset, so the rows are empty (zero). However, this condition arises not because the model is absolutely perfect, but because the test data only contains one class (Suitable). Therefore, it is reasonable that the precision, recall, and f1-score all = 1.00 (100%).

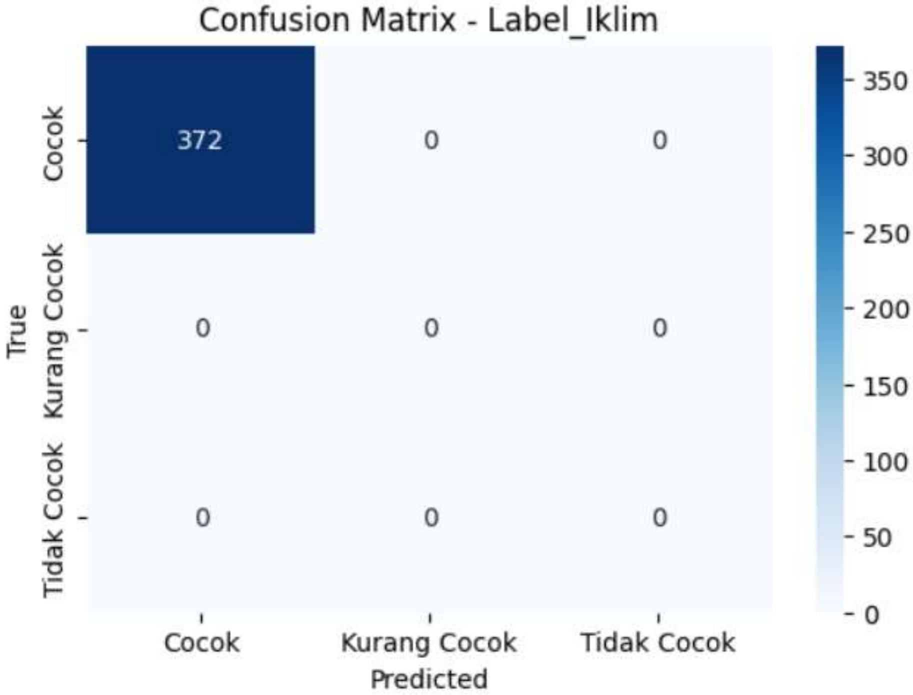

Figure 8. Confusion Matrix Label_Iklim

Discussion

The analysis of the experimental results proceeded by evaluating the performance of the recognition and prediction models independently, followed by assessing their integration within the final system. Overall, the findings indicate that each component achieved its intended functional objectives, although several limitations were identified.

The YOLOv9 recognition model demonstrated strong detection capability, achieving an mAP@50 of 0.8932, supported by precision and recall values of 0.7664 and 0.8092, respectively. These metrics confirm the model's ability to reliably identify rice varieties under typical field-image conditions. However, the confusion matrix revealed that the model occasionally misclassified background regions as valid objects, indicating sensitivity to visual noise and insufficient background differentiation—a common challenge in agricultural imagery where texture and foliage patterns may resemble target features.

The Naïve Bayes suitability classifier was evaluated using two label schemes. For Label_Ketinggian, the classifier attained 78% accuracy, demonstrating moderate discriminative ability based on elevation-derived features. Misclassification of several Tidak Cocok instances as Kurang Cocok suggests overlapping feature distributions and limited separability within the input space. For Label_Iklim, the classifier achieved perfect accuracy; however, the result cannot be generalized due to the single-class nature of the test set, which prevented evaluation under more diverse climatic conditions.

The integration of both models into the Gradio-based dashboard confirmed that the recognition and prediction components can operate sequentially within a unified workflow. The system successfully generated variety identifications followed by suitability assessments. Nonetheless, intermittent failures occurred during variety recognition within the dashboard environment. Analysis showed that these issues were attributable not to deficiencies in the trained models but to inconsistencies in Gradio's internal image preprocessing pipeline, which altered image encoding prior to inference and, in some cases, caused the YOLOv9 model to fail to detect objects.

In summary, although several limitations emerged—primarily related to background sensitivity and dataset imbalance—the study successfully developed an operational system capable of providing automated rice variety identification and agroclimatic suitability prediction. These results demonstrate the feasibility of integrating computer vision and probabilistic classification techniques for practical agricultural decision support.

D. Conclussion

This study presented the development and integration of two artificial intelligence models YOLOv9 for rice variety recognition and Naïve Bayes for climate suitability prediction into a unified decision-support system for Bandung Regency. The recognition model demonstrated strong accuracy across most rice varieties, and the suitability classifier produced consistent predictions aligned with agroclimatic conditions. The integration of both models into an interactive dashboard enabled automated image-based identification followed by suitability assessment, illustrating the system's practical utility for supporting data-driven decision-making in rice cultivation. Future work may consider the following enhancements: (1) Dataset Expansion: Increase image diversity and quantity, particularly for low-performing varieties (e.g., Inpari NutriZinc and Baroma), and collect data across broader illumination and growth conditions. (2) Finer-Scale Climate Data: Utilize village-level or microclimate data rather than regency-level monthly averages to improve suitability precision. (3) Additional Agronomic Variables: Incorporate soil characteristics, pH, and water availability to produce more comprehensive predictive outputs. (4) Hyperparameter Optimization: Explore alternative training configurations (e.g., learning rate, batch size, epochs) to further improve model robustness and class-wise performance. These improvements are expected to enhance model accuracy and strengthen the system's applicability within precision agriculture frameworks.

E. Acknowlegment

The author would like to express sincere appreciation to the Ministry of Research, Technology, and Higher Education of the Republic of Indonesia (Kementerian Riset, Teknologi, dan Pendidikan Tinggi—RISTEKDIKTI) for the support, guidance, and contributions that enabled the successful completion of this research. The author is grateful for the institutional assistance, resources, and academic environment provided throughout the study, which significantly facilitated the development of the integrated YOLOv9 and Naïve Bayes system for rice variety–climate suitability analysis.

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