Indonesian Journal of Agronomy

ISSN 2085-2916 | e-ISSN 2337-3652
Indonesian J. Agron., *51*(1), 80-90, April 2023
DOI: https://dx.doi.org/10.24831/ija.v51i1.44111

Research Article

Rice variety identification system based on drone images to support seed certification process

Ardo Ardiyansah [1], Ahmad Zamzami [2,*], and Wulandari [3]

[1] Bachelor Student, Department of Agronomy and Horticulture, Faculty of Agriculture, IPB University, Jl. Meranti, Kampus IPB Darmaga, Bogor 16680, INDONESIA
[2] Departement of Agronomy and Horticulture, Faculty of Agriculture, IPB University, Jl. Meranti, Kampus IPB Darmaga, Bogor 16680, INDONESIA
[3] Departement of Computer Science, Faculty of Mathematics and Natural Sciences, IPB University, Jl. Meranti, Kampus IPB Darmaga, Bogor 16680, INDONESIA
* Corresponding author (✉ ahmadzamzami@apps.ipb.ac.id)

ABSTRACT

Utilization of technology can be a solution in the process of supervising certified seeds, especially at the stage of field inspection, which is faster and more efficient. This study aimed to develop a drone image-based rice variety system to support the inspection process for seed certification. The research was conducted from March – July 2022. The rice plants of IPB 3S and Inpari 32 varieties located in Karawang, West Java were observed for their agronomic characteristics. The images of the two varieties were taken using a drone and augmented and cropped. The overall image obtained was 80% used as training data, 20% as data validation, and 10% as test data. The variety identification system was built using a model by applying the convolutional neural network (CNN) algorithm. The performance of the model was observed through accuracy, precision, recall, and F1-Score. All agronomic characters justified that the two varieties used were different. This study produced three CNN models that could accurately identify the varieties of IPB 3S and Inpari 32 with an accuracy rate of 99.52% to 100%. Drone imaging is prospective for field inspection process of seed certification.

Keywords: CNN, deep learning, image processing, seed production, unmanned aerial vehicle

Edited by:
Maryati Sari

***Received**:*
9 November 2022
***Accepted**:*
12 April 2023
***Published online**:*
27 April 2023

Citation:
Ardiyansah, A., Zamzami, A., & Wulandari. (2023). Rice variety identification system based on drone images to support seed certification process. *Indonesian Journal of Agronomy*, *51*(1), 80-90.

INTRODUCTION

Indonesia is faced with challenges in terms of large-scale monitoring of certified seeds due to government policy on the reduction in Seed Inspectors in the certification process. Apart from that, another challenge was conveyed by Zamzami and Budiman (2019) that the field/planting inspection activities by seed inspectors have so far been carried out manually so their implementation is time-consuming. The field (plant) inspection in the seed certification process aims to obtain certainty that the seed to be produced in an inspection area conforms to the description of the variety to be produced. This process includes the correctness and purity of the variety. The correctness of varieties is obtained through the process of identifying varieties which will also be the basis for determining the purity of plants on seed production.

Utilization of technology such as drone imaging can be a solution in the process of inspection of certified seeds, especially during the field inspection stage. Reckling et al. (2021) reported that visual analysis of unmanned aerial vehicle (UAV) imagery can be used to verify the locations of known plants and semi-automated detection of plant species can use a neural network object detector. In addition, Zamzami and Budiman

(2019) also concluded that the use of drones has proven to have the potential to be used in the rice seed certification process.

The identification of rice varieties has the opportunity to be carried out based on digital image results from drones which are then followed by deep learning computational techniques through automatic digital image object recognition programming algorithms using the Convolutional Neural Network (CNN) method. Ilahiyah and Nilogiri (2018) succeeded in distinguishing 20 plant species using CNN with an average accuracy of the classification results reaching 85%, while the accuracy of identification managed to reach 90% obtained from testing 40 images. Furthermore, Suartika et al. (2016) stated that CNN is one of the applications of the principles of artificial neural networks that have high network depth in their architecture so that they are classified as deep neural networks (DNN). Image processing techniques can be used to classify citrus varieties (Qadri et al., 2019), almond seeds (Borraz-Martínez et al., 2022), and varieties of corn seeds (Tu et al., 2022). This study aimed to develop a rice plant variety identification system for field inspection of drone image-based seed certification by applying the CNN algorithm to support the seed certification process.

MATERIALS AND METHODS

Research site

The research was conducted from March to July 2022. The materials used were the rice plants of the IPB 3S variety and the Inpari 32 variety which were located in Karawang Regency, West Java Province. Data processing and analysis were carried out at the Department of Agronomy and Horticulture, Faculty of Agriculture, Bogor Agricultural University.

The equipment used in this study consisted of a meter, leaf color chart, DJI Phantom 4 Drone, laptop (RAM 12 GB, Intel Core i5 7200U) smartphone (RAM 2GB, android 7 or above which is this specification that supports the running of the DroneDeploy application. This research used Android 7, DroneDeploy application, Agisoft Metashape, Microsoft Excel, SAS, Miniconda3, and Google Colaboratory.

Data acquisition

Identification of agronomic characters was carried out on 2 (two) rice varieties, namely the IPB 3S variety and the Inpari 32 variety. The two varieties have significant differences, especially in the height of the plants and the number of productive tillers as stated in the Ministerial Decree. Observations were made at 6 points/plots for each variety, each point/plot consisting of 5 sample plants. Observations were made twice, namely at the age of the rice plants 8 WAP (week after planting) and 10 WAP. Variables or characters observed included plant height, number of tillers, leaf color using Rice Leaf Color Chart, number of productive tillers, panicle length, and number of grain^{-1} panicles.

Image acquisition was carried out at the age of 8 WAP and 12 WAP. On 8 WAP, the weather conditions were sunny and cloudy accompanied by wind so it affected the image condition, both the brightness level and the position of the rice. At 10 WAP the weather was quite cloudy and foggy. The acquisition was carried out with the DJI Phantom 4 drone with a planned flight path using the DroneDeploy application. The flight is arranged with a composition of 9 m altitude, 80% overlap, and 75% overlap.

Data processing

Pre-processing data from aerial photography results is done by making ortho mosaic maps and image augmentation. The proportion of drone image data from ortho mosaic maps in this study is 90% model-building process data and 10% test data, process data is divided into 80% training data and 20% validation data.

The model was built using two methods consisting of the transfer learning method, namely using the existing architecture for feature extraction and the CNN architecture development method. The transfer learning method utilizes the MobileNetV2 architecture which produces two models, namely the model trained by selecting standard validation data (Model 1) and the model trained by selecting validation data using the Stratified K-Fold Cross Validation/CV method (Model 2). Meanwhile, the CNN architectural development method produced one model, namely CNN containing nine layers consisting of six layers in the feature extraction layer and three layers in the classification layer with the selection of validation data using the Stratified K-Fold CV method (Model 3).

Agronomic character data obtained from field identification were analyzed using a statistical t-student test at a 5% significance level. The results of the analysis were then compared descriptively to the evaluation of the model made. In model evaluation, the predicted output results from the CNN model were recapitulated using the confusion matrix and classification report which contained accuracy, precision, recall, and F1-Score.

RESULTS AND DISCUSSION

Agronomic character observation

Observation of agronomic characters on IPB 3S and Inpari 32 varieties was carried out manually to justify the differences between the two varieties. The agronomic characters of rice varieties aged 8 WAP showed that the two varieties tested had significant differences in all the characters observed (Table 1). The IPB 3S variety had an average height of 118.10 cm, significantly different from Inpari 32 which is only 89.30 cm (average). The results of observations on other characters, namely the number of tillers and leaf color scale, the Inpari 32 variety had a higher average value than the IPB 3S variety, namely 29.67 tillers and the color scale was 3.45 while the average value of the number of tillers and the color scale the leaves of the IPB 3S variety respectively were 14.33 and 3.08.

Table 1. The average value of rice varietal characters at 8 weeks after planting.

Variety	Plant height	Number of tillers	Leaf color (scale)
IPB 3S	118.10a	14.33b	3.08b
Inpari 32	89.30b	29.67a	3.45a
Pr > |t|	<.0001**	<.0001**	0.0004**

Note: **= significant at α = 5% based on the t-student test.

Agronomic characters of rice varieties aged 10 WAP also showed that the two varieties tested, IPB 3S and Inpari 32, had significant differences in all the characters observed (Table 2). The IPB 3S variety had a plant height of 127.57 cm which was significantly different from the Inpari 32 variety which is only 99.33 cm. The number of tillers of the Inpari 32 variety was 31.67 tillers and it was significantly different from the IPB 3S variety which only had 16.70 tillers. In addition, the average number of productive tillers in the Inpari 32 variety was significantly higher than the IPB 3S variety, which was 21.57 tillers while the IPB 3S variety had 12.23 tillers. Observations on panicle length and the number of grain^{-1} showed that IPB 3S had significantly higher panicle length and the number of grain^{-1} than Inpari 32. The differences in the characters of the two varieties observed were by the descriptions of each variety which indeed also showed significantly different characters.

Table 2. The average value of rice varietal characters at 10 weeks after planting.

Variety	Plant height (cm)	Number of tillers	Number of productive tillers	Panicle length (cm)	Number of grain per panicle
IPB 3S	127.57a	16.70b	12.23b	30.63a	233.80a
Inpari 32	99.33b	31.67a	21.57a	23.30b	147.67b
Pr > |t|	<.0001**	<.0001**	<.0001**	<.0001**	<.0001**

Note: **= significant at α = 5% based on the t-student test.

Pre-processing data

Data pre-processing begins with data processing from drone image acquisition to an orthomosaic map. This was done to combine drone images into a single image. Furthermore, cropping was carried out with a grid measuring 224 × 224 pixels which aims to collect data on rice varieties and obtain images that were more focused on the subject of classification while reducing the file size. The results of the cropping process produced images that weer more uniform in size (Figure 1). Irawaty et al. (2017) stated that Drones/UAVs can be equipped with multispectral cameras for agricultural research, and the data obtained is in the form of image displays. UAV can now be considered a new measurement tool, allowing it to be used in the process of retrieving geospatial data, with sufficient specifications and a camera that has a good resolution (Wardana et al., 2019).

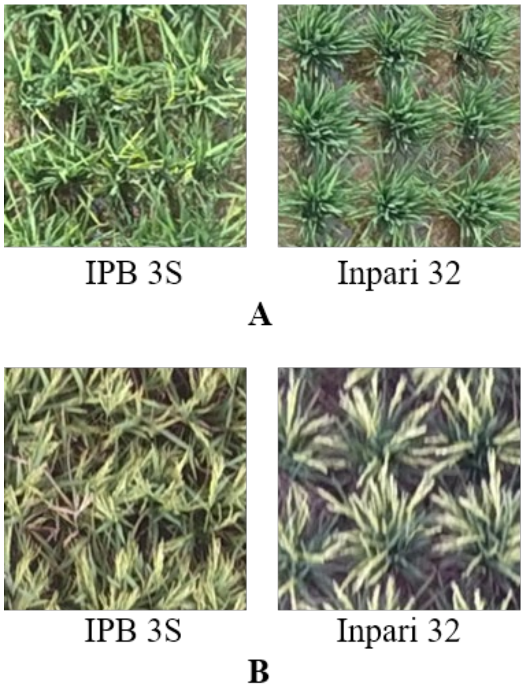


Figure 1. Image cropping results of rice, at 8 WAP (A) and 10 WAP (B).

CNN model development requires large amounts of training data to improve the performance of the built model. If the data available for the learning process (learning) for the CNN model is too little, then this results in a high risk of overfitting (Dhira, 2021). Overfitting is a condition in which almost all data that has gone through the training process reaches a good percentage, but there is a discrepancy in the prediction process (Santoso & Ariyanto, 2018). Augmentation and cropping of the training data in this study resulted in a dataset with a total of 12,600 images (data not shown). The dataset was divided into 1260 images for test data and 11,340 images for process data consisting of 9072 images for training data and 2268 images for validation data. Each dataset contained the number of images with the same proportion between IPB 3S and Inpari 32 varieties.

CNN model development

The transfer learning method used MobileNetV2 to produce Models 1 and 2 by modifying the MobileNetV2 architecture. Modifications were made to the classification layer where the prediction layer was changed from 1,000 ImageNet classes to two nodes according to the number of classes, namely varieties. In addition, at the beginning of the architecture, the command rescales input pixel value to (-1,1) was also added. Next was the adaptation phase, namely freezing at the MobileNetV2 feature extraction layer so that the architecture was trained only at the classification layer. The final step was fine-tuning, which retraining the entire architecture by unfreezing the feature extraction layer and training it with a smaller learning rate which aimed to get lower loss.

Model 3 consists of a convolution layer and a pooling layer, each of which was carried out three times in the order of convolution 1, pooling 1, convolution 2, pooling 2, convolution 3, and pooling 3. The first convolution layer was created with an input image size of 224 × 224 × 3, 8 filters, kernel size = 3 × 3, and ReLu activation. The 2nd convolution layer was performed with 16 filters, kernel size = 3 × 3, and ReLu activation. The third convolution layer was performed with 32 filters, kernel size = 3 × 3, and ReLu activation. While the pooling layers 1, 2, and 3 were carried out using the max pooling method with pool size = 2 × 2, strides = 2. Images that had gone through the feature extraction layer and produce mapped and dimensionally reduced features were then these featured into the classification layer. The classification layer consisted of a flattened layer, a dense 128 layer with ReLu activation, and a dense layer 2 with SoftMax activation. The flattened layer functioned to reduce feature dimensions so that they became one-dimensional features as fully connected inputs.

Before the model went through the training process, the model was compiled with the following parameters: the optimizer parameter used in the three models was Adam, with a learning rate of 0.001 except in the fine-tuning phase of the transfer learning method, which was 0.00001. Furthermore, the Epoch parameter was 20 epochs, the loss function parameter was categorical cross-entropy, and the metric parameter was accuracy. In the training process (using only data from the two varieties used), the checkpoint strategy was implemented using the ModelCheckpoint function with monitoring validation accuracy. This strategy functioned to save the model every time a better validation accuracy was obtained and will not save if the validation accuracy decreases so that when the validation accuracy value decreases until the end of the epoch, namely the 20th epoch, the model obtained is the best model during the training process.

Validation in model 1 used standard validation data that was randomly selected from 11,340 images. The selection was made by selecting random numbers via Microsoft Excel as many as 1260 numbers then the image with the name of the number chosen was moved to the validation data folder. This process was divided into 2 processes, namely the adaptation phase and the fine-tuning phase with 5 and 15 epochs, respectively. More epochs in the finetuning phase was designed to deepen learning with a lower learning rate. Figure 2 shows the changes in the loss and accuracy graphs resulting from the training and validation processes.

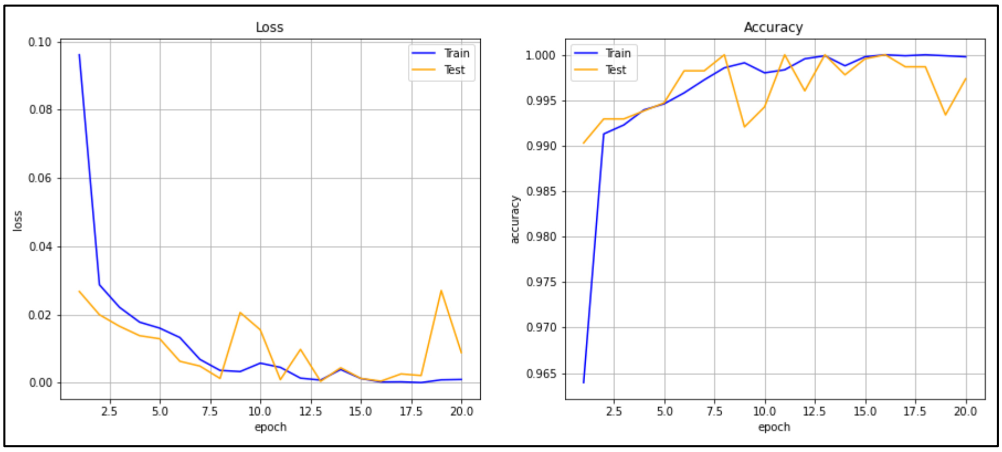


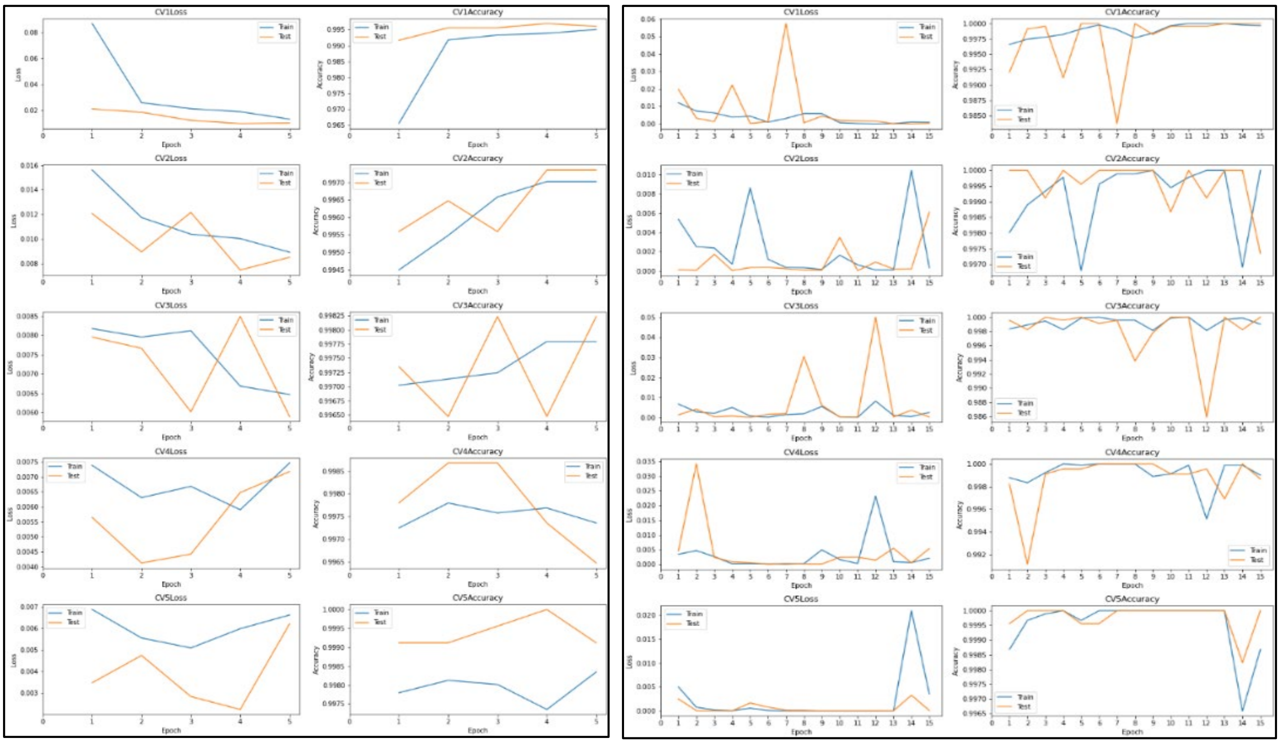
Figure 2. Changes in loss and accuracy Model 1.

In machine learning, an epoch means one complete cycle of the learning process. Thus, the more epochs selected implies the lower the loss value in training data and validation/test data, conversely, the accuracy value increases with increasing epochs, although it still shows a little fluctuation that needs to be watched in the future. The decrease in the loss value that occurs in the training data shows a more stable decrease compared to the decrease in the loss value in the validation data. In addition, the increase in the accuracy value of the training data also shows a more stable increase compared to the increase in the validation data. This is because the CNN algorithm performs a network training process on training data. The lowest loss value was achieved on the training data which was 0.00005 and the validation data was 0.0004. The highest accuracy achieved on training data and validation data is 100%. However, the validation accuracy value has been achieved in the 8th epoch so the model used in the test using test data is the 8th epoch model with a loss value in the training data of 0.0036 and validation data of 0.0013 with an accuracy of 99.86 % on training data and 100% on validation data. Validation was achieved in the 8th epoch because the training process uses the Model checkpoint function. This function saves the model every time validation accuracy is obtained its better than before and will not save if validation accuracy decreased.

Validation on model 2 used a stratified k-fold CV developed by Pedregosa et al. (2011) with a splits value of 5. This divided the entire process data, totaling 11,340 images, into 80% training data and 20% validation data per CV. In addition, this process was divided into 2 processes, namely the adaptation phase and the fine-tuning phase. The process of training and validation of the two phases was carried out 5 times CV per phase respectively with the division of 5 epochs in the adaptation phase and 15 epochs in the fine-tuning phase. According to Lasulika (2017), CV is one of the methods used to determine the average success of a system by looping by randomizing input attributes so that the system is tested for several random input attributes.

The changes in the loss and accuracy graphs resulting from the training and validation processes are shown in Figure 3. In Figure 3A it is shown that the loss and accuracy change values at the beginning of each CV are a continuation of the previous CV loss and accuracy values. This continuous process of changing loss and accuracy values can be caused by the fact that the transfer learning method utilizes the MobileNetV2 weights that have been previously trained using the ImageNet dataset. This causes this model to be very good. The graph in Figure 3B shows that in the fine-tuning phase, the loss and accuracy values for each CV continue from each CV in the adaptation phase. The results of the validation can be seen in Figure 4. The graphical movement of accuracy, precision, recall, and F1-score values from the first to the 5th CV shows the accuracy, precision, recall, and F1-score values which continue to increase during the adaptation phase training process. Accuracy, precision, recall, and F1-score at the end (CV 5) of the adaptation phase reached 1 or 100%. In the fine-tuning phase, the values for accuracy, precision, recall, and F1-score look stable at 1 or 100%.

Validation on model 3 used stratified k-fold cross-validation. Figure 5 shows the changes in the loss and accuracy graphs resulting from the training and validation processes. The graph shows that the change in loss and accuracy values at the beginning of each CV repeats from the beginning, so it can conclude the model performance of each CV. According to Yadav and Shukla (2016) that CV is a general method used to evaluate the predictive performance of several different models. The validation results can be seen in Figure 6. The graphical movement of accuracy, precision, recall, and F1-score values from the first to the 5th CV shows stable values ranging from 0.98941 to 0.99559.



A **B**

Figure 3. Changes in loss and accuracy of Model 2. Adaptation phase (A) and finetuning phase (B).

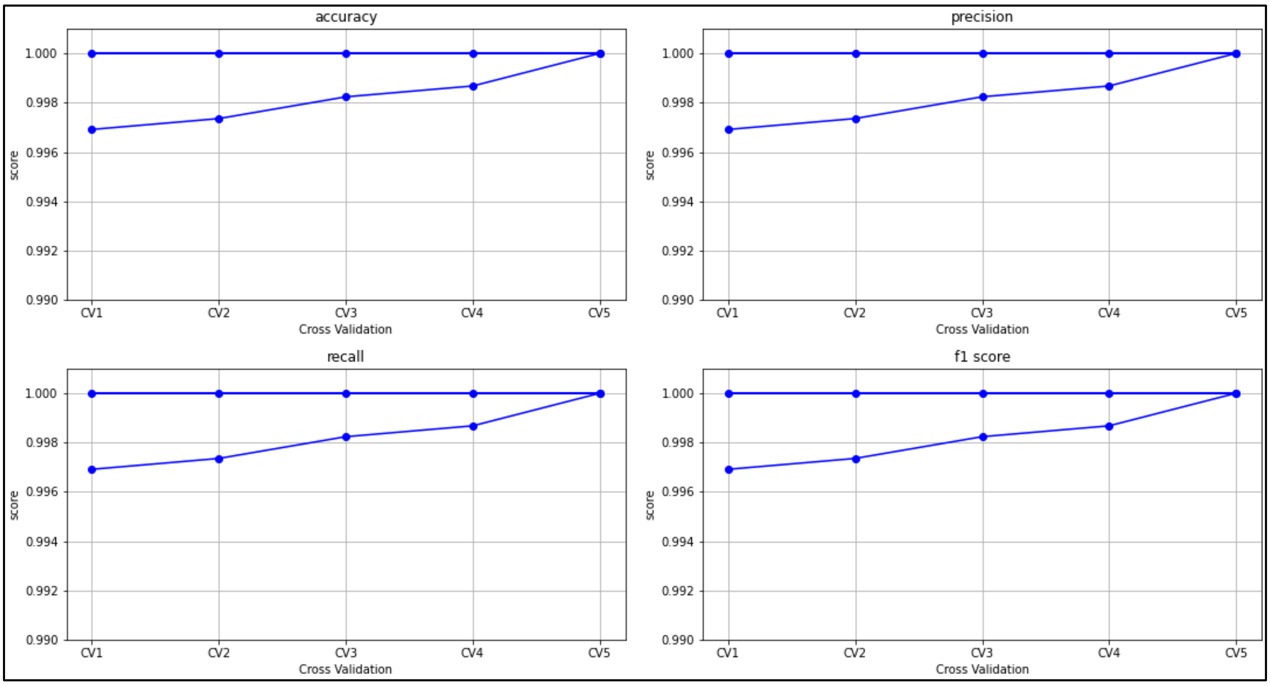


Figure 4. Recapitulation of Model 2 validation.

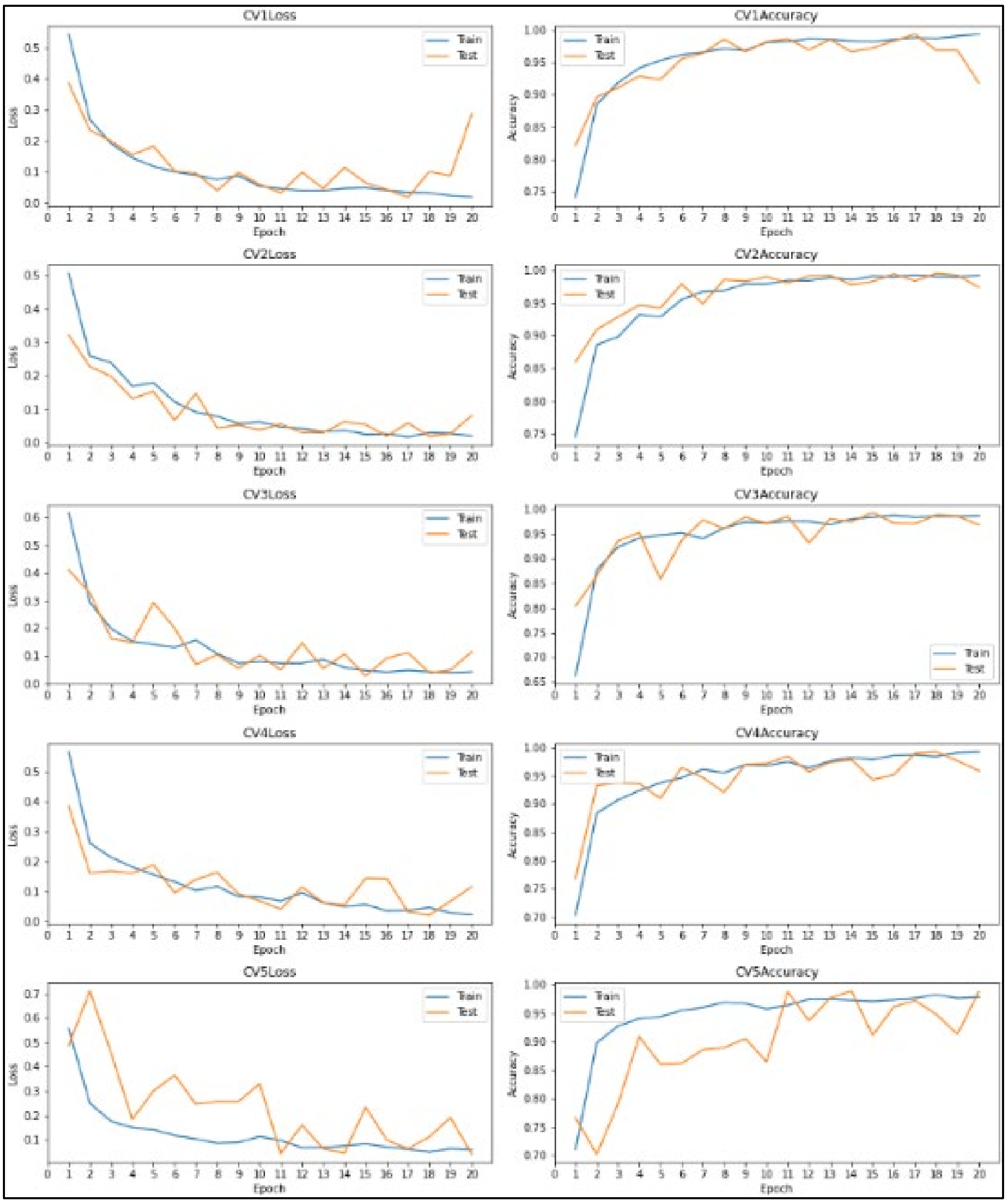


Figure 5. Changes in loss and accuracy Model 3

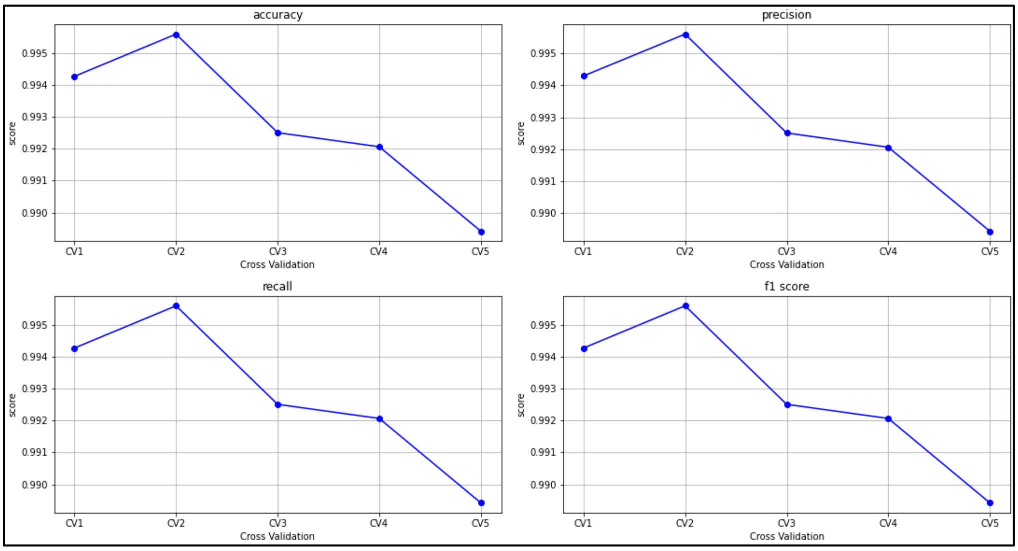


Figure 6. Recapitulation of Model 3 validation.

CNN model evaluation

The recapitulation of the test results can be seen in the results of the confusion matrix (Figure 7). Based on the results of the confusion matrix, it can be seen that the prediction accuracy value in model 1 was 99.52%, the prediction accuracy value in model 2 was 100%, and the prediction accuracy value in model 3 was 100%. In addition to the accuracy value, the evaluation results in the form of precision, recall, and F1-score can be seen in Table 3. This is inline with Yamashita et al. (2018) that CNN is suitable for processing with input in the form of images.

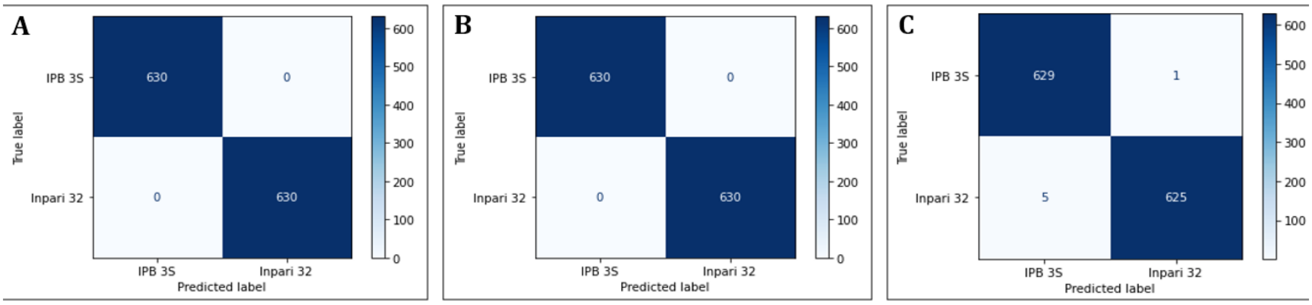


Figure 7. The prediction results of the confusion matrix use test data. Evaluation of Model 1 (A), Evaluation of Model 2 (B), and Evaluation of Model 3 (C).

Table 3. Summary of model evaluation values.

Label	Precision	Recall	F1-Score
	Model 1		
IPB 3S	1.00	1.00	1.00
Inpari 32	1.00	1.00	1.00
Average	1.00	1.00	1.00
	Model 2		
IPB 3S	1.00	1.00	1.00
Inpari 32	1.00	1.00	1.00
Average	1.00	1.00	1.00
	Model 3		
IPB 3S	0.9921	0.9984	0.9953
Inpari 32	0.9984	0.9921	0.9952
Average	0.9953	0.9952	0.9952

In the present experiment, descriptive comparisons between models suited with agronomic characters. IPB 3S variety and Inpari 32 variety could be predicted by 3 CNN models with accuracy between 99.52% to 100%. Therefore, this model can be used to verify the correctness of varieties in the inspection process of plantings in the context of seed certification. This is in line with what was stated by Sari et al. (2021) that imagery from drones (RGB) can be used in rice monitoring. The CNN model is also reported for the detection and classification of plant pests and diseases (Domingues et al., 2022) and corn seeds in the context of testing purity (Bi et al., 2022). However, further development is still needed to increase the number of varieties, especially those that have similar morphological characteristics. In addition, the phenotypic variation of a variety also needs to be added as model training data in order to reduce misclassifying varieties of different growing stages that are detected as different images. It is known that rice growth is determined by soil fertility (Peng et al., 2017) and irrigation (Herdiyanti et al., 2021).

CONCLUSIONS

The development of a rice variety identification system using IPB 3S and Inpari 32 resulted in three models. Model 1 was the MobileNetV2 transfer learning model with validation data selection using stratified k-fold CV with 100% accuracy, Model 2 was the MobileNetV2 transfer learning model using standard validation data with 100% accuracy, and Model 3 was the development of the CNN architecture using stratified k validation. -fold CV with 99.52% accuracy. Drone imaging is prospective for field inspection process of seed certification of rice. Further research is needed to incorporate different stages of rice growth.

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