Classification of Sri Lankan Paddy Varieties using Deep Learning Techniques

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Abstract

Rice is a highly consumed staple food in Sri Lanka. From farming phase to distribution phase of paddy, classification of paddy is becoming vital as it provides efficiency to the planning, production, sales and consumption. In Sri Lanka, the evaluation of the classification of paddy varieties is typically overseen by the Rice Research and Development Institute (RRDI). Traditionally, paddy identification is done manually by human inspectors, ensuring some level of accuracy but requiring significant manpower, time, and subjective judgment. This research seeks to transform the categorization of paddy varieties in Sri Lanka. This paper provides an approach to identifying and classifying paddy variety in paddy sample with the help of image processing and CNN model. For this approach, 10 varieties of paddy samples were collected from Rice Research and Development Institute. With these samples a dataset of more than 10,000 images were captured and used in this research. Image preprocessing involved cropping, scaling, and noise removal to standardize the data. Experiments were conducted with nine different CNN models, iterating through various architectures and training parameters to optimize performance. The experiment was performed on ten rice categories to evaluate the suggested solution. The accuracy of classification is of 93.69%.

Keywords: Convolutional Neural Network (CNN), Depp Learning, Paddy Classification

I.INTRODUCTION

Rice is favorable and highly consumed food in Sri Lanka. Rice is one of the highly consumed and staple food of Sri Lanka. Around 3.1 million tons of rough rice (paddy) are grown every year to meet about 95% of the country's demand. Since more than 1.8 million farmers and their families depend on rice production, rice holds a unique importance compared to other agricultural products in Sri Lanka (Anon, n.d.).

The accuracy of identifying paddy is one of the most important factors when classifying rice varieties. The use of paddy varieties differs depending on the purposes. Different varieties of rice are used for the production of many value-added products, including food varieties. Therefore, rice variety identification is very important for consumers (Golpour et al., 2014). In addition, the price and grade of rice are decided by its commercial value, genetic characteristics, and quality factors, which depend on the type of rice variety.

Currently, the classification of paddy is performed manually, typically through visual inspection by experienced and well-trained individuals. However, this approach has significant drawbacks, including time consumption and unreliability due to inconsistencies and the involvement of unskilled technicians. Moreover, results may vary from person to person leading to subjective results. Therefore, there is a pressing need for a more efficient and accurate method of paddy variety classification. The review of literature shows that both Machine Learning (ML) and Computer Vision (CV) have been extensively employed across various domains, offering a fast, accurate, nondestructive, and cost-effective substitute for automated paddy classification processes. Deep learning techniques have superseded statistical methods in computer vision due to their enhanced accuracy in tasks such as object identification and image recognition (Kiratiratanapruk et al., 2020).

While research on the classification of paddy varieties is limited, the identification of rice varieties has been extensively studied using external parameters such as shape, size, color, and texture (Cinar, 2019). For example, Singh and

Chaudhury (2020) classified rice grains based on morphology, color, texture, and wavelet features, using image pre-processing techniques followed by a cascade network classifier. Similarly, Nagoda and Ranathunga (2018) employed support vector machines (SVM) and image processing methods to classify rice samples based on physical properties like color and texture, achieving a segmentation accuracy of 96% and a classification accuracy of 88%. Cinar (2019) also identified seven morphological features for classifying two different rice species. Several machine learning models, including Logistic Regression (LR), Multilayer Perceptron (MLP), SVM, Decision Trees (DT), Random Forest (RF), Naïve Bayes (NB), and K-Nearest Neighbor (KNN), were tested for classification accuracy, with success rates ranging from 88.58% to 93.02%. Additionally, Chatnuntawech et al. (2018) proposed a deep CNN algorithm for classifying rice varieties, using spatial–spectral data from two datasets, and achieved a mean classification accuracy of 91.09%. Their study also employed hyperspectral imaging to examine rice seeds in a consistent orientation.

Despite the limited research on paddy classification, there is a clear need to focus specifically on classifying Sri Lankan paddy varieties. The review of existing literature highlights the scarcity of research on Sri Lankan paddy and the lack of application of emerging deep learning methodologies. Therefore, this study aims to evaluate the effectiveness of deep learning algorithms in classifying Sri Lankan paddy varieties.

II.LITERATURE REVIEW

Artificial Neural Networks (ANN) have significant role for rice classification. For instance, Pazoki et al. (2014) used ANN Multi-Layer perceptron (MLP) and neuro-fuzzy networks to classify five rice varieties in Iran along with UTA feature selection algorithm to fine-tune the classifiers. The analysis used 24 color features, 11 morphological properties, and four shape factors to classify rice grains. The screening is proved to have a rate above 99% for both approaches.

There are numerous ML techniques that are available for the classification purposes. Arora et al., (2020) used different image processing algorithms and ML algorithms for rice grain classification using various parameters of individual rice grains like major axis, minor axis, eccentricity, length, breadth, etc. Relevant features of the rice grains have been extracted using various image processing algorithms. The rice grain images have been classified using different machine learning algorithms, such as LR, DT, NB, KNN, RF and Linear Discriminant Analysis (LDA) classifiers. They proposed future directions for incorporating additional features like chalkiness and moisture content analysis to ensure good quality rice is delivered.

While various ML algorithms have achieved significant classification accuracy, ensemble learning approach is also gaining momentum for classification problems. Ensemble Learning can achieve better performance than a single model alone by combining various models. It can be applied to various ML tasks including classification. Setiawan & None (2024) used ensemble learning methods to classify rice grains based on image features. The study compared various machine learning algorithms, ultimately finding that Bagging meta-estimator improved classification accuracy by combining predictions from multiple base estimators. They utilized Bagging meta-estimator to aggregate decisions from multiple base classifiers, reducing model variance and improving classification consistency. By applying this approach to various grain features, ensemble method achieved consistent classification accuracy across different paddy varieties.

Most studies on image-based paddy classification have primarily focused on color, morphology, and shape features. By using near-infrared hyperspectral imaging technology, both spatial and spectral information, as well as morphological features, can be captured. Jin et al. (2022) combined near-infrared hyperspectral imaging with traditional machine learning methods and deep learning models to classify rice seed varieties. This non-destructive imaging technique captures high-resolution spectra, enabling the detection of even subtle differences in paddy grain features, which leads to accurate classification across various rice varieties. Among conventional machine learning methods, SVM performed well, while in deep learning, LeNet, GoogLeNet, and ResNet models showed effective identification. Deep learning methods significantly outperformed conventional machine learning algorithms, with most models achieving classification accuracies exceeding 95%.

In another study, Qiu et al. (2018) employed a near-infrared hyperspectral imaging system with two different spectral ranges *(380–1030 nm and 874–1734 nm)* to classify four rice seed varieties. The study compared the performance of various discriminant models, including KNN, SVM, and CNN. Models utilizing the spectral range of 874–1734 nm outperformed those built with the 380–1030 nm range, with CNN outperforming both KNN and SVM.

Rajalakshmi et al. (2024) achieved 97% accuracy in classifying 13 southern Indian paddy varieties — such as *Yanaikomban, Swarna Masoori, Sivapu Kowuni, and Mapillai Samba*—using a Deep Neural Network (RiceSeedNet) combined with traditional image processing techniques. They also demonstrated RiceSeedNet's potential to achieve 99% accuracy in classifying eight paddy grain varieties from a public dataset. The study utilized two datasets: one containing 13,000 images of southern Indian paddy varieties (1,000 images per variety), and another with 8,000 images from an open-source benchmark dataset (1,000 images per variety). In the research of Paddy seed variety classification using transfer learning based on deep learning, Jaithavil, D. et al. (2022) used three pre-trained models VGG16, InceptionV3, and MobileNetV2 to classify three paddy varieties. Compared with various other two models Inception-v3 showed the highest accuracy and least test loss with 83.33% and 28.41% respectively

Few other recent studies have been successful in classifying paddy varieties. For instance, Ansari, N. et al. (2021), presented a rapid inspection method to classify three paddy varieties using color, texture and morphological features and k-nearest neighbors, support vector machine, and partial least squares-discriminant analysis (PLS-DA) algorithm. Where the classification accuracy using PLS-DA, SVM-C, and KNN model was 83.8%, 93.9%, and 87.2% respectively. In another study, Uddin, M. et al. (2021) proposed a computer vision-based system for non-destructive paddy seed variety identification, crucial for maintaining seed purity in agriculture and industry. To address challenges like illumination variations during image capture, the study introduced a modified histogram-oriented gradient (T20-HOG) feature. Combined with Haralick and traditional features, these were refined using the Lasso technique and used to train a feed-forward neural network (FNN) for accurate variety prediction demonstrated 99.28% accuracy in identifying paddy grain types.

Anami, B.S. et al. (2020) proposed a deep convolutional neural network (DCNN) framework for automatic recognition and classification of various biotic and abiotic stresses in paddy crops. The pre-trained VGG-16 CNN model was used to classify stressed images during the booting growth stage. The trained models achieved an average accuracy of 92.89% on the held-out dataset, demonstrating the technical feasibility of using the deep learning approach. The proposed work finds applications in developing decision support systems and mobile applications for automating field crop and resource management practices. The approach is applicable to 11 classes of biotic and abiotic stresses from five different paddy crop varieties.

III.METHODOLOGY

The methodology applied for this study is illustrated in Figure 01 below.

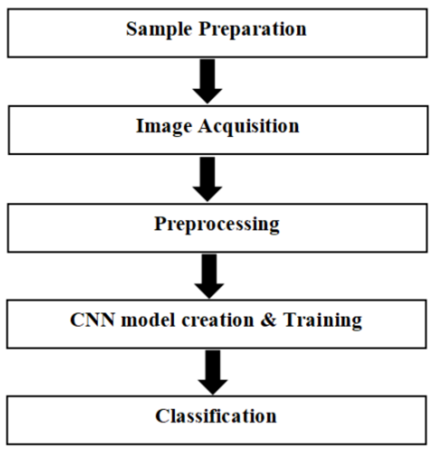


Figure 01: Applied Methodology

G. Sample Preparation

Although many different varieties of paddy are available today, ten common paddy grain samples were chosen for this study using a convenient sampling method. 100grams of paddy grain samples from eight common Sri Lankan Paddy varieties (At 309, At 362, At 373, Bg 300, Bg 352, Bg 359, Bg 374, Bw 367) and two Sri Lankan traditional varieties (Kahawanu, Madathawalu) were selected for the data set preparation. They were obtained from Rice Research and Development Institute (RRDI), Bathalagoda, Ibbagamuwa (Figure 02).

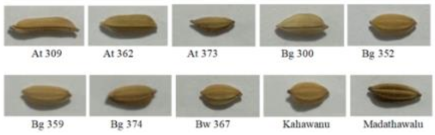


Figure 07: Samples images of ten paddy varieties

H. Image Acquisition

The paddy grains were first cleaned to eliminate impurities, and random samples from each variety were selected for image acquisition. 1000 images of each paddy varieties were captured in the same lightning condition and same fixed frame by an iPhone 14 pro camera. Each image of a paddy seed was acquired with the seed placed centrally and horizontally, with the seed body rotated along the horizontal axis.

I. Preprocessing

First, images of paddy were cropped and scaled to a uniform size of 500 x 250 pixels to standardize all the images and noise removal was done using bilateral and non-local filters where, bilateral filtering was effective for preserving edges and non-local filtering was effective for various noise types (Figure 03).

Figure 08: Preprocessed Images a) Raw image captured from camera b) Image after Cropping c) Image after Noise Removal

Bilateral filtering is an advanced image processing technique used to smooth images while preserving edges, making it ideal for applications where edge preservation is important. Bilateral filtering maintains the integrity of edges while reducing noise and smoothing the image.

Bilateral filtering is defined by:

$$BF[I]_P = \frac{1}{W_P} \sum_{q \epsilon S} G_{\sigma_s}(||p-q||)\, G_{\sigma_r}(I_p - I_q)\, I_q$$

where:
$BF[I]_P$ is the filtered image at pixel p
I_p and I_q is are the intensities at pixels p and q respectively.
S is the spatial domain of the image.
$G_{\sigma_s}(||p-q||)$ is the spatial Gaussian kernel.
$G_{\sigma_r}(||I_p - I_q||)$ is the range Gaussian kernel.
W_P is the normalization factor:

$$W_P = \sum_{q \epsilon S} G_{\sigma_s}(||p-q||)\, G_{\sigma_r}(I_p - I_q)$$

The bilateral filter operates by combining both spatial and range kernels, where the spatial kernel depends on the Euclidean distance between pixels p and q, with σ_s controlling the spatial extent of the filter and the range kernel depends on the intensity difference between pixels p and q, with σ_r controlling the range of intensity values that influence the filtering. The filtered image at a pixel is computed as a weighted sum of neighboring pixels, with the weights determined by both the spatial distance and intensity difference. This method effectively smooths regions with similar intensities while maintaining the sharpness of edges. Bilateral filtering provides better edge preservation than other filtering methods like Gaussian filtering, which often blurs edges, or median filtering, which can lose finer details. By reducing noise while retaining sharp edges, bilateral filtering ensures that important features are maintained, leading to more accurate classification.

J. Model Creation and Training

Since CNN has shown proven accuracy in various image-based classification problems due to their ability to capture spatial hierarchies of features through convolutional layers, this study employed CNN for the classification of paddy (Alzubaidi et al., 2021). Single paddy image was used to train the CNN model for the paddy classification. Dataset was split into three sets: training, validation and testing for accurate evaluation. Several own baseline CNN Models were created and trained on the training set, with performance tracking and hyperparameter optimization guided by the validation set. Iterative refinement was done using the validation set to consistently improve the model's performance.

In the development of a CNN model, the initial attempts utilized basic architectures with dropout layers to prevent overfitting, followed by the addition of batch normalization for improved training stability. The third iteration introduced preprocessed images with noise removal. Subsequent models incorporated further refinements, including dropout, regularization techniques, L2 regularization, and a learning rate scheduler to enhance model robustness and performance. In the final models, the primary focus was on significantly expanding the dataset to improve the model's effectiveness.

The best-performing CNN model, as determined by our experiments, was composed of convolutional layers, each followed by activation functions, batch normalization, and pooling layers. Initially the input layer of the architecture processed images of size 500x250x3. The first convolutional layer applied 32 filters of size 3x3 with ReLU activation, followed by a 2x2 max pooling layer. This structure was consistently applied across subsequent layers, with the number of filters progressively increasing to 64, 128, 256, and finally 512, enabling the model to extract increasingly complex features. Batch normalization was used after each convolutional layer to enhance training stability, and dropout layers were incorporated to mitigate overfitting. The model concluded with a fully connected layer comprising 512 neurons, regularized with L2, and a dropout rate of 0.5. The final softmax output layer classified the input into one of 10 categories.

K. Evaluation

In the development of a CNN models, each model designed with different architectural complexities. The comparison of these models was conducted to identify the most effective paddy identification task. Performance evaluation was carried out using performance metrics, including accuracy, precision, F1 score, recall and AUC.

Accuracy: The percentage of correctly classified instances in the dataset is measured generally as accuracy. The number of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) is used to calculate it.
The accuracy is defined by:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

Precision: Defined as the percentage of correctly identified positive instances among all predicted positive instances. It is particularly important when the cost of false positives is high, as it indicates the reliability of the positive predictions.
The precision is defined by:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

Recall: quantifies the percentage of real positives that the model accurately detected. When ignoring positive cases (false negatives) is more crucial than mislabeling negatives as positives, it is extremely significant.
The recall is defined by:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

F1 score: The average mean of recall and precision combined.
The F1 score is defined by:

$$\text{F1 Score} = \frac{2 \times (\text{Precision} \times \text{Recall})}{\text{Precision} + \text{Recall}}$$

AUC: Area Under the Curve evaluates the model's ability to distinguish between positive and negative classes. It reflects the probability that a randomly chosen positive instance is ranked higher than a negative one. Higher AUC values indicate better performance, with 1.0 being perfect and 0.5 indicating no discrimination.

IV.RESULTS & DISCUSSION

A. Model 1

The global minimum of the loss function was reached at the 30th epoch. Despite this, the results were suboptimal; the validation accuracy was 74.2%. A significant oversight in this training phase was the use of raw data, rather than preprocessed data, which likely impacted the model's performance negatively. This experience underscores the importance of data preparation in building effective machine learning models, as preprocessing can significantly influence the accuracy and efficiency of the training process.

B. Model 2

The global minimum of the loss function was again reached at the 30th epoch. However, despite these adjustments, the results did not meet expectations. The validation accuracy was recorded at 62.5%. Similar to our initial attempt, the model was trained using raw data instead of preprocessed data, which adversely affected its performance. This experience further highlighted the critical importance of data preprocessing in training CNN models, as the lack of it can lead to significant discrepancies in performance metrics.

C. Model 3

The global minimum of the loss function was achieved at the 80^{th} epoch. Despite these improvements in data preprocessing, the performance metrics indicated that the training was not optimal. The validation accuracy was relatively low at 47.5%. This suggested issues in the model architecture or parameter settings that were not addressed merely by preprocessing the data. The significant loss indicates that further model evaluation and adjustments are necessary to improve its effectiveness.

D. Model 4

with the global minimum of the loss function being reached remarkably early at the 10^{th} epoch. Despite these extensive changes, the training outcomes were highly unsatisfactory. The model achieved a validation accuracy of only 17%. This performance indicates a significant misalignment in the model's training process or architectural setup. These results underscore the need for a thorough review and recalibration of the model's configuration and training strategy.

E. Model 5

The model achieved a validation accuracy of 83%, indicating a substantial enhancement in its ability to generalize from the training data to unseen validation data. The improvements in image quality, along with careful preprocessing and effective model architecture, contributed to the much-improved performance metrics. This iteration demonstrates the critical importance of high-quality data and appropriate model tuning in developing effective deep learning systems.

F. Model 6

The results led to a notable improvement in the model's performance, achieving a validation accuracy of 76%. This represents a significant enhancement, confirming the effectiveness of the learning rate scheduler in optimizing the training process and the L2 regularization in improving the model's performance. This iteration underscores the utility of adaptive learning rate mechanisms and regularization techniques in boosting the accuracy and efficiency of machine learning models, especially in scenarios involving complex datasets and model architectures.

G. Model 7

The increase in dataset size proved to be highly beneficial, as reflected by a validation accuracy of 75.42%, the highest achieved across all above iterations.

H. Model 8

Finaly the same model 7 was trained using our whole dataset and the model achieved a validation accuracy of 93.69%. The substantial improvement in performance with the expanded dataset highlights the critical role of data volume in training machine learning models. A larger dataset provides a more comprehensive representation of the variability and complexity inherent in real-world data, thereby enhancing the model's ability to learn and generalize effectively. This milestone underscores the importance of both quality and quantity in dataset composition when aiming to improve model accuracy and robustness.

The performance of our models was affected by the quality of the dataset, image conditions, and the architectural choices made during model development. Models 1 and 2, which used raw, unprocessed images captured under varying lighting conditions and angles, struggled with noise and irrelevant features due to wide backgrounds and inconsistent image conditions, leading to poor identification and suboptimal results. In Model 3, preprocessing steps such as resizing and cropping were introduced, but the model still underperformed, indicating that the presence of wide backgrounds continued to overshadow the seeds. To address these issues, Models 5 through 8 utilized a standardized image capture process, where all images were centrally aligned, uniformly cropped, and preprocessed using bilateral filtering for edge detection and non-local means filtering for noise reduction. The architectural improvements in later models, including the addition of dropout, L2 regularization, and learning rate scheduling in Models 5 and 6, further helped to prevent overfitting and enhance generalization.

To ensure the trained model is correctly identifies the paddy seed, 30 paddy images were used for the prediction which are not used for train, test, or validate the model. The best performed model identified all images and other models identified few.

The result is summarized and presented below in Table 01 and Table 02.

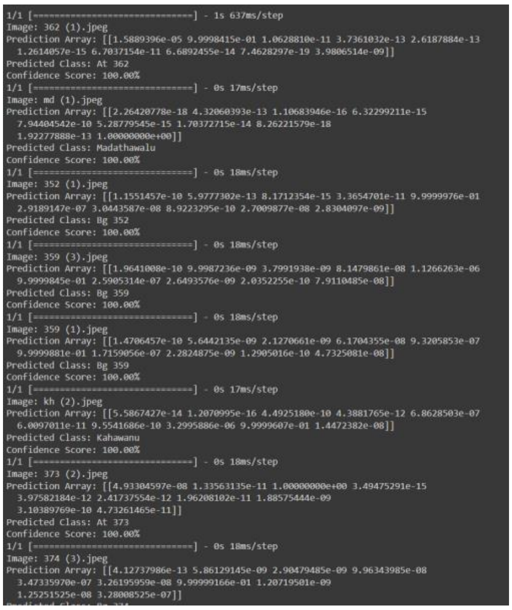
Table 01: Summary of different CNN models which are trained using proper dataset

Model	Epoch	Learning rate	Validation Accuracy	Train Accuracy	Test Accuracy	F1 Score	Precision	recall	AUC
5	60	0.001	83%	99.5	78.25	0.11	0.14	0.11	0.51
6	60	Dynamically changed	76%	100%	55%	0.1	0.18	0.11	0.47
7	60	Dynamically changed	75.42%	100%	82.25%	0.11	0.11	0.12	0.51
8	60	Dynamically changed	93.69%	100%	89.75%	0.94	0.95	0.94	0.99

Table 02: Summary of different CNN models which are trained using improperly captured images

Model	Epoch	Learning rate	Validation Accuracy
1	100	0.0001	74.2%
2	40	0.001	62.5%
3	100	0.0001	47.%
4	60	0.001	17%

Figure 03 illustrates the prediction of paddy seeds by Model 8.



```
1/1 [==============================] - 1s 637ms/step
Image: 362 (1).jpeg
Prediction Array: [[1.5889396e-05 9.9998415e-01 1.0628810e-11 3.7361032e-13 2.6187884e-13
  1.2614057e-15 6.7037154e-11 6.6892455e-14 7.4628297e-19 3.9806514e-09]]
Predicted Class: At 362
Confidence Score: 100.00%
1/1 [==============================] - 0s 17ms/step
Image: md (1).jpeg
Prediction Array: [[2.26420778e-18 4.32060393e-13 1.10683946e-16 6.32299211e-15
  7.94404542e-10 5.28779545e-15 1.70372715e-14 8.26221579e-18
  1.92277888e-13 1.00000000e+00]]
Predicted Class: Madathawalu
Confidence Score: 100.00%
1/1 [==============================] - 0s 18ms/step
Image: 352 (1).jpeg
Prediction Array: [[1.1551457e-10 5.9777302e-13 8.1712354e-15 3.3654701e-11 9.9999976e-01
  2.9189147e-07 3.0443587e-08 8.9223295e-10 2.7009877e-08 2.8304097e-09]]
Predicted Class: Bg 352
Confidence Score: 100.00%
1/1 [==============================] - 0s 18ms/step
Image: 359 (3).jpeg
Prediction Array: [[1.9641008e-10 9.9987236e-09 3.7991938e-09 8.1479861e-08 1.1266263e-06
  9.9999845e-01 2.5905314e-07 2.6493576e-09 2.0352255e-10 7.9110485e-08]]
Predicted Class: Bg 359
Confidence Score: 100.00%
1/1 [==============================] - 0s 18ms/step
Image: 359 (1).jpeg
Prediction Array: [[1.4706457e-10 5.6442135e-09 2.1270661e-09 6.1704355e-08 9.3205853e-07
  9.9999881e-01 1.7159056e-07 2.2824875e-09 1.2905016e-10 4.7325081e-08]]
Predicted Class: Bg 359
Confidence Score: 100.00%
1/1 [==============================] - 0s 17ms/step
Image: kh (2).jpeg
Prediction Array: [[5.5867427e-14 1.2070995e-16 4.4925180e-10 4.3881765e-12 6.8628503e-07
  6.0097011e-11 9.5541686e-10 3.2995886e-06 9.9999607e-01 1.4472382e-08]]
Predicted Class: Kahawanu
Confidence Score: 100.00%
1/1 [==============================] - 0s 18ms/step
Image: 373 (2).jpeg
Prediction Array: [[4.93304597e-08 1.33563135e-11 1.00000000e+00 3.49475291e-15
  3.97582184e-12 2.41737554e-12 1.96208102e-11 1.88575444e-09
  3.10389769e-10 4.73261465e-11]]
Predicted Class: At 373
Confidence Score: 100.00%
1/1 [==============================] - 0s 18ms/step
Image: 374 (3).jpeg
Prediction Array: [[4.12737986e-13 5.86129145e-09 2.90479485e-09 9.96343985e-08
  3.47335970e-07 3.26195959e-08 9.99999166e-01 1.20719501e-09
  1.25251525e-08 3.28008525e-07]]
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Figure 03: Prediction of paddy seeds by model 8

X. CONCLUSION

Deep learning technologies are now commonly used in various sectors of agricultural production and industrial food production. In this paper, we aim to develop CNN models to classify10 paddy varieties from a dataset of nearly ten thousand images of paddy seeds. We investigated nearly 1000 data samples in each paddy variety for training and testing models. Several CNN models were evaluated and compared in order to obtain a model that had the best performance. the highest classification accuracy obtained was 93.69%. The preliminary work presented in this paper could be further enhanced by focusing on clustering to identify and classify different paddy varieties in a single image.

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