Classification of Various Rice Varieties Using Convolutional Neural Network

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***Abstract*—Rice is India's fastest growing crop, and as the population expands, so does demand for rice. The large percentage of Asian countries cultivate and export rice. Various rice types have been produced based on the dietary culture of the people. While at the same time, quality of food is a primary issue, thus we extract rice intrinsic traits using computer vision algorithms. Four distinct CNN Architectures are used to examine the goods. It can learn from millions of datasets while keeping the highest accuracy rate. Furthermore, this convolution approach attempts to extract high-level information from the entire image, and these elevated features are then used to add the image's edges. Image processing techniques are used with neural networks to increase the proposed model's training accuracy over the manual procedure. Jasmine, Basmati, Arborio, Ipsala, and Karacadag rice cultivars were used to categorise the picture collections. Each of these types has 15000 photographs, for a total of 75000 photographs used in training and testing. The highest accuracy score determines the best image classifier. The outcome of the proposed model assumes a better performance of 98.06% in detecting rice types. These findings indicate that utilising a Deep Learning technique, rice variety identification and classification can be done directly.**

***Index Terms*—Neural Network, object recognition, image analysis, morphological characteristics, Rice classification.**

I. Introduction

Rice is a cereal grain that is cultivated and harvested all over the world. There are hundreds of distinct types of rice, which may be categorised into numerous groups depending on variables such as form, size, coloration, and temperature conditions. The length of the grain is a frequent technique to categorise rice. Long-grain rice features grains that are longer than they are wide, as the name implies. Short-grain rice, in contrary, has shorter and broader grains than long-grain rice. Another way to classify rice is by the color of the grain. White rice is the most common type of rice, rather than brown rice. Some rice varities are somewhat pale and some are a mix of white and brown. There are many other ways to classify rice, including by the regions where they are grown, the specific varieties of rice plants that are used to produce the grain. No matter how it is classified, rice is a versatile and important food crop that is enjoyed by people all over the world.

Deep learning is an effective methodology for classifying rice types based on form, texture, and morphological characteristics. It is feasible to reliably categorise rice types based on their physical properties using trained convolutional neural networks (CNNs). We employed deep learning techniques to classify rice kinds based on their photos in this work. The dataset included pictures of many rice kinds such as Arborio, Basmati, Ipsala, Jasmine, and Karacadag. This can provide valuable information for rice breeders, farmers, and researchers interested in the genetic diversity of rice. The classification accuracy of deep learning models can be further improved by incorporating additional features, such as grain size, color, and texture, into the training data. This approach can help to improve the understanding of rice diversity and facilitate the development of more resilient and productive rice varieties.

On the validation set, the model attained an accuracy of 98.06%, indicating its ability to reliably categorise rice types based on their photos. The findings of this study show that deep learning has the capacity to categorise rice types, which can be valuable for quality control and supply chain management in the rice business.

Image classification is the task of assigning a label to an input image, based on its visual content. In the case of rice varieties, this would involve training a model to identify the different types of rice based on their visual characteristics, such as color, shape, and texture. This can be accomplished using deep learning, a type of machine learning that involves training a neural network on large amounts of data. It has the ability to automatically learn complex, hierarchical representations of the input data. This makes it possible to achieve high levels of accuracy on a wide range of tasks, including object recognition and scene understanding.

Once we have a sufficient dataset of tagged pictures, we can train a deep learning model on it. This is often achieved by the application of a (CNN), a type of neural network especially developed for image classification tasks. CNN is trained on labelled pictures via backpropagation, which modifies the network's internal weights and biases to reduce the difference between predicted and true labels. This can be accomplished manually by having people annotate the photographs, or automatically by employing machine learning algorithms to collect the appropriate information from the images.

To perform this task, a deep learning model would be trained on a large dataset of images of different rice varieties. The model would then be able to recognize the visual patterns and characteristics associated with each variety and make accurate predictions on new, unseen images.Using deep learning for rice variety classification has the potential to provide more accurate and efficient results than traditional methods, and can be easily integrated into existing systems and processes. After the CNN is trained, it can be used to classify new, unseen images of rice varieties. Given an input image, the CNN will output a probability distribution over the different classes, indicating the likelihood that the image belongs to each class. We can then choose the class with the highest probability as the predicted label for the input image.

It can help rice farmers and researchers more accurately identify different rice types, which can improve crop yield and quality. It can also assist in the development of new rice varieties and the study the rice genetics. Faster breakthroughs and development in image processing software and hardware helped build frameworks for evaluating the quality of processed and raw foods in numerous research initiatives (Abdullah et al. 2000)[1]. Recently developed computer technologies have provided a substantial contribution to the sorting, checking, and grading of rice's quality (Parmar et al. 2011)[2]. Most studies have found that the morphological properties of rice are of particular interest to researchers.

The identification and classification of rice with accuracy and efficiency offers considerable potential when using CNN-based image classification. This study's goals were to build a highly efficient approach based on CNN and image processing to automatically identify productive rice varieties from the fields.

II. Literature Survey and Background Work

Shantaiya and Ansari (2010) [3] developed a digital image analysis technique based on morphological, textural, and colour factors to distinguish between the six variations of rice seeds. A combination of nine morphological and six colour along with two textural features are assessed with the intention of distinguishing.Modified ANN based classifier was created to recognize unidentified grain types, with the mean accuracy of around 84.88%.

S. Sonnadara et. al. in the study [4], created a model that uses computer vision techniques to classify 9 distinct rice variety. From each rice seed colour picture sample, several algorithms collected 13 Morphological, six colour, and 15 textural attributes. A trained system with an appropriate dataset significantly enhanced classification accuracy. With a merged feature set, the total classification accuracy was 92%.

Pazoki et al. (2014) [5] suggested a model for classifying five major Iran rice grain variants. For categorization, 24 colour, 11 morphological, and 4 form parameters of Each rice grain was depicted in colour in the pictures that were found. The accuracy rates for the MLP and neuro-fuzzy systems were 99.46 and 99.73%, respectively.

Precision for rice variety of various types, Khunkhenttt and Remsuqngnen (2014) [6] used computerised image analysis to discover pure breeding rice seed without destroying it. The form and colour of rice are essential components in agricultural reproduction and quality assessment. is the proper for the classification rates for the two stages are 98 percent for ”excellent” rice seeds and 92 percent for ”bad” rice seeds. Genuine breeding rice seeds account about 82%.

Neelama and Gupta (2015) [7] developed the computer Vision method to identify rice and categorization. In this example, the training procedure was based on the Levenberg-Markov model. Marquardt. With an accuracy of roughly 89.7%, the model was trained latter evaluated on a set of various parameters.

Devi et al. (2017) [8] introduced a computer vision system for assessing and sorting rice grains that takes physical and compound properties into account. With an accuracy of 94.28 percent, the suggested algorithm used MatLab to implement means of separated features to grade, analyze the qualities of rice.

III. Materials and Methods

A. Dataset Discription

The datasets we utilised included five rice kinds collected in Turkey: Arborio, Ipsala, Karacadag, Jasmine, and Basmati. The files contain 75,000 images in total, with 15,000 shots of each type of rice grain. The images in the databases are RGB images of 250 by 250 pixels (Figure 2). The datasets also contain a second feature with 12 morphological, 90 colour, and 4 form features. Figures 3 and 4 display the 12 morphological characteristics as well as the four shape traits. The formulae are shown in Figure 4, and the shape factor is calculated using the SF. The 90 various colours were also created using variations of the YCbCr (Y-Luminance, Cb - Chroma blue, Cr - Chroma red), XYZ, and RBG to HSV colour spaces.

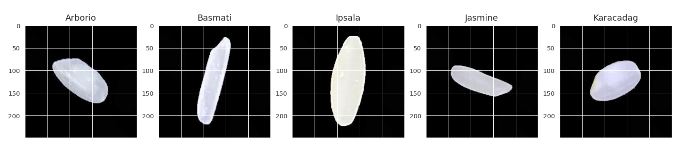

Fig. 1. Images from the dataset

Morphological Structures	
Minimal Axis Length	Convex Area
Perimeter	Eccentricity
Solidity	Equivalent Diameter
Extent	Aspect ratio
Roundness	. Compactness
. Area	. Major Axis Length

Fig. 2. Morphological Features

TABLE I
LITERATURE SURVEY OF THE RELATED WORKS

AUTHOR	No. of samples	Features Used	METHOD	ACCURACY
Shantaiya and Ansari	60	Color, Morphological	Image Analysis	84.83% Accuracy
Silva and Sonnadara	500	Textural, Color, Morphological	MLP	92% Accuracy
Pazoki	450	shape, color	MLP and Neuro fuzzy	99.46% , 99.73% Accuracy
Khunkhett and Remsungnen	250	color, Morphological, Textural	Digital Image and computer vision	Good seed 98.3% Pure Breeding Seeds 82.6% Accuracy
Devi et al.	4	shape, color, Morphological, Textural	Computer vision	94.28% Accuracy

Shapes	Equations
SF_1	$\frac{Major\ Axis\ Length}{Area}$
SF_2	$\frac{Minimal\ Axis\ Length}{Area}$
SF_3	$\frac{Area}{\left(\frac{Major\ Axis\ Length}{2}\right)^2 \times \pi}$
SF_4	$\frac{Area}{\frac{Major\ Axis\ Length \times Minimal\ Axis\ Length}{2} \times \pi}$

Fig. 3. Shape Features and there equations

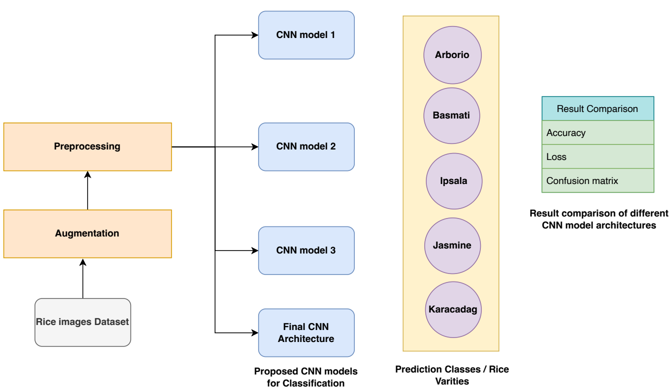

Fig. 4. Workflow diagram of our methodology

B. Proposed Methodology

For the purpose of identifying rice varities, the CNN architecture is proposed, which is efficient for classifying any inputted image frame into 5 classes respectively.

C. Preprocessing and Augmentation

All the pixel values in the images of the dataset were normalized between 0 and 1. This is often done because deep learning models can have difficulty learning from inputs that have very large or very small values, or that have very different scales for different features. By normalizing the input data, we can help the model learn more effectively and potentially improve its performance. Additionally, normalization can also help reduce the amount of memory and computational resources required to train a deep learning model.

To improve the quantity and variety of a dataset, deep learning frequently uses data augmentation techniques. This is done by applying a series of transformations to the existing data, such as cropping, scaling, rotating, flipping, or adding noise. By augmenting the data, we can help the model learn more effectively and potentially improve its performance. Data augmentation can also aid in preventing overfitting, a problem that frequently arises in deep learning where a model performs well on training data but badly on unobserved data. By augmenting the data, we can introduced additional variations in the data, which can help the model generalize better to unseen data.

1) Convolution Neural Network (CNN) Architecture: Because of its capacity to pull characteristics from layers inside themselves and utilise those features to learn and categorise, CNN networks are often employed. The architecture proposed in this study consisted of the following layers: The first layer that is the input, which is a starting layer in all standard designs, receives the raw input pictures, which are generally 224x224 normalised RGB images of rice.

Convolutional layer is the second layer and it applies a set of 64, 7x7 filters with stride length as 2 to the input images to extract features from them. The outputs of these filters are called feature maps. By using a max pooling operation with a 2x2 window, the third layer of the architecture, or the pooling layer, decreases the dimensionality of the feature maps. This is accomplished by calculating the maximum value for each 2x2 feature map subregion. The layers are then paired up as how residual networks are connected in next convolution layer. The matrix produced shows that there are three levels: two of kernel size 3 x 3, 64 and 256 filters, and a third layer of kernel size 3 x 3, 64 filters, repeated three times to represent the layers between pool, or 2. Similar steps are taken until the fifth convolutional layer, at which point average pooling is used at the fully connected layer and softmax is then used for classification. The output layer is the final layer and it produces the output predictions for our model. The output layer has 5 neurons, one for each possible class of rice variety, and each neuron produces a score indicating the likelihood that a given input belongs to a particular rice class.

Fig. 5. Model Architecture

IV. Results and discussion

1) Proposed CNN Model: Our Proposed CNN Model Give a accuracy score of 98.06% on Validation dataset. The graph 1 (figure 5) and 2 (figure 6) shown are the curve for model accuracy and loss which shows a smooth curve and convergence rate without any overfitting. The comparision table (Table 2) show the results of previous 3 CNN model.

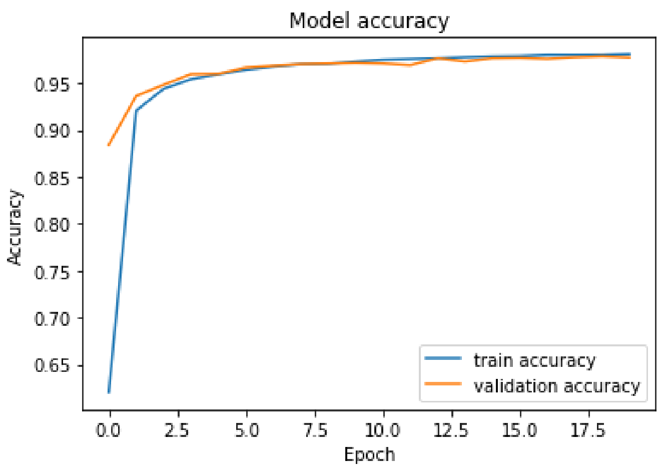

Fig. 6. Model Accuracy

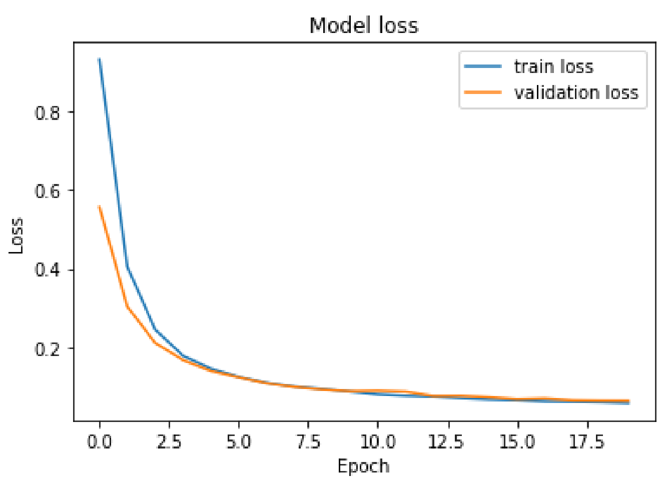

Fig. 7. Model Loss

We use the model to predict output class by given a random input from validation set and the model predicted it correctly as shown in figure 9.

	precision	recall	f1-score	support
0	0.99	0.95	0.97	2250
1	0.98	0.98	0.98	2250
2	1.00	0.99	1.00	2250
3	0.97	0.98	0.98	2250
4	0.96	0.99	0.97	2250
accuracy			0.98	11250
macro avg	0.98	0.98	0.98	11250
weighted avg	0.98	0.98	0.98	11250

Fig. 8. Classification report

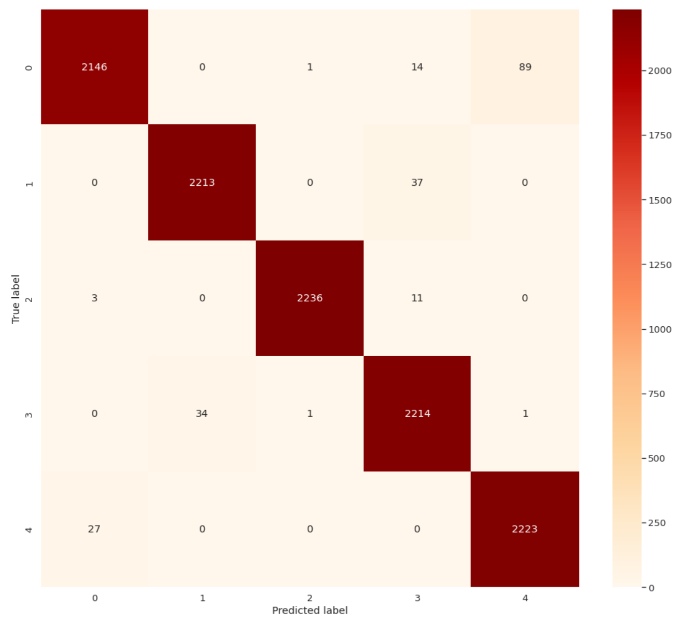

Fig. 9. Confussion Matrix

V. Conclusion

Deep learning techniques can be effectively used for the classification of rice varieties. The use of convolutional neural networks (CNNs) has shown promising results in accurately identifying different rice varieties based on their visual appearance. Additionally,the classification of the images of five different rice varieties employed a number of CNN models. Five different types of rice, each with a dataset of 15,000 photos, were identified using an unique CNN model that we built. In order to more accurately assess the quality, texture, colour, and other attributes of the rice, we trained four distinct CNN models and chose the one with the highest accuracy rate during the testing phase. Based on the effectiveness and precision of all four strategies, we chose the best model. On the validation dataset, the final Model has the highest accuracy of the other models, at 98.06%. We improved the classification of rice types using the CNN model. The suggested model's results consider the improved performance in finding the precise rice varieties that are 98% accurate.

TABLE II
VARIOUS CNN MODEL COMPARISON

Model Architectures	Train, Test, Validate %	No. of Epochs	Training Accuracy	Validation Accuracy
Architecture 1	80%, 20%	20	79.6	92.5
Architecture 2	80%, 20%	20	97.7	99.7
Architecture 3	80%, 20%	20	96.8	98.6
Final CNN Architecture	80%, 15%, 15%	20	98.09	98.06

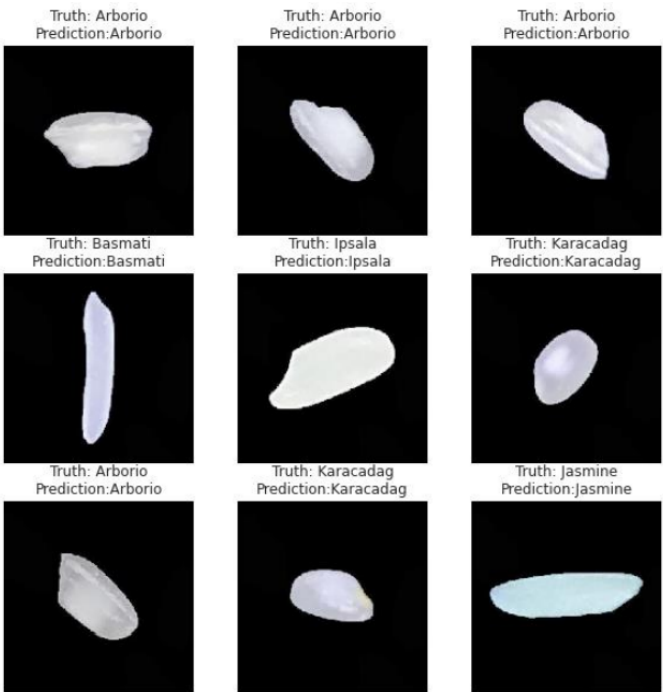

Fig. 10. Predicted Classes

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