Image Classification of Rice Varieties Using CNN, LSTM and Ensemble Model

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***Abstract*—Classification plays an important role in the commodities market of rice production, as it provides the correct way to estimate the value of the grains concerning their categories. Several research works have been carried out in this domain, and we propose a machine learning system that incorporates Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) and ensemble models for classification. It also involves the integration of LSTM, a form of Recurrent Neural Network (RNN), to improve system performance. We used an open-source dataset consisting of 75,000 images of five different types of rice. Our approach correctly predicted the exact variation of the input sample with an accuracy rate of 97.6%. The proposed rice classification technique presents a feasible solution for practical applications due to its reasonable cost and runtime performance.**

Keywords– Rice type classification, CNN model, LSTM model, Ensemble model

I. INTRODUCTION

Rice is the source of food energy for more than half the people of the entire world. Rice has important roles in both global food security and economic stability. India ranks as the second largest rice producer in the world. Rice cultivation forms the backbone of the agricultural sector, and ensuring accurate and efficient classification of rice varieties is very crucial to maintaining quality standards in the market. There are many varieties of rice with different physical characteristics and nutritional values; hence, there should be proper classification for efficient distribution to ensure that the farmers get a good return and that the consumers get value for their money [21].

Being a staple and reasonably priced, rice turns out to be one of the most consumed food by people of underdeveloped nations, growing the demand of cultivation of rice [2]. Because of higher production, traditional rice categorization depends on manual inspection, which is labor-intensive and susceptible to human fallibility; hence, inefficient [6]. Therefore, for betterment in terms of accuracy and scalability concerning the agricultural sector, this project was undertaken to automate rice classification through advanced deep-learning techniques. A number of rice varieties were considered in this regard, and the dataset prepared in this regard includes Arborio, Basmati, Ipsala, Jasmine, and Karacadag.

The process would start with the preprocessing of data: scaling, normalization, and label encoding of data into an analyzable format. Then, further on, a Convolutional Neural Network (CNN) is used to extract the spatial features that are the visual features within rice images, concerning each variety of different types of rice, since it outperforms all traditional machine learning methods [6]. While CNN achieves considerable accuracy, the project studies further enhancement through the addition of a Long Short-Term Memory (LSTM) network that captures temporal dependencies and patterns within the sequences of images. Combining the two models into an ensemble amalgamates their strengths, hence improving the overall architecture with respect to both classification performance and generalization across diverse rice types.

Many studies have already proved the application of rice variety classification using deep learning. Dr. S. Ponmalar, M. Devavaishnee, and M. K. Indhu Priya [10] classified various rice varieties by using VGG-19 and AlexNet deep learning models. Rice disease detection can also be made besides classifying rice varieties. Q. Yao, Z. Guan, Y. Zhou, J. Tang, Y. Hu, and B. Yang [5] applied a Support Vector Machine (SVM) on shape and color texture features for the detection of rice diseases. A study was made by detecting and classification of rice leaf diseases using YOLOv7 by Haque, E., Paul, M., Rahman, A., Tohidi, F., Islam, J. [20]. Many other studies have been carried out relating to advancements in Agriculture. In our study, a robust and trustworthy method was developed using CNN and LSTM for rice variety classification, which will be helpful in optimizing the market distribution and controlling the quality standards. This would help farmers in the process of selling by classifying the rice effectively.

II. LITERATURE REVIEW

Several studies are being conducted in the field of agriculture, with rice classification being one of them. The following papers have been referenced for their quality datasets and implementation methods. A detailed review of recent work on rice classification is provided below.

A study was conducted using image classification to classify a dataset of rice leaf diseases, such as Brown Spot Rice disease (BSR), Leaf Smut Rice disease (LSR), and Bacterial Leaf Blight disease (BLB). Among different image processing technologies, the best performance was achieved using the Random Forest algorithm, with an accuracy of 69.44% [1]. The low accuracy was attributed to the small dataset size.

20-40% of crop production loss is due to rice diseases. Yibin Wang, Haifeng Wang, and Zhaohua Peng used the ADSNN-BO model, based on the MobileNet structure, to identify rice diseases and plan prompt treatment. To tune the hyperparameters of the model, they used the Bayesian optimization method. The results showcased a test accuracy of 94.65% [3].

Using a dataset of 1,600 images collected from Punjab, India, a CNN-based system for diagnosing rice illnesses identified Hispa with 92.83% accuracy [15]. The small dataset size and challenges in gathering real-time data with varying image resolutions were among the limitations.

Rice variety categorization was improved by using a combination of CNN and hyperspectral imaging techniques, which automatically extracted features from spatio-spectral data [17]. However, limitations of this technique included the need for a large, labeled dataset and the computational demands of hyperspectral data processing.

Another study combined Principal Component Analysis (PCA) and the Canny edge detection method for rice classification and quality analysis, achieving 92.3% and 89.5% accuracy, respectively [18]. However, the system's reliance on simple morphological features hindered its ability to capture complex changes. Additional accuracy improvements could be achieved using advanced techniques such as the General Hough Transform (GHT).

An AI-powered rice disease classification system, using Deep CNN and SVM on a dataset of 1,080 images covering nine diseases, achieved 97.5% accuracy [19]. However, the model's performance was poor on smaller datasets, and its reliance on large datasets for weight updates limited its overall effectiveness.

Although YOLOv7 faced challenges with image and data quality as well as dataset size, it was still able to detect rice leaf disease more accurately than YOLOv5. Issues related to data quality and the model's dependence on a large, diverse training dataset affected its accuracy [20].

A fast rice variety identification system relied heavily on spectral data, which may not capture all variations in rice properties. It struggled to distinguish between rice varieties with highly similar spectral features, ultimately failing to surpass 98.41% accuracy using an SVM classifier [21].

In another study, six varieties of rice were classified with accuracies ranging from 95.2% to 97.4%, with the Logistic Model Tree classifier performing the best at 97.4% [23]. However, using a cell phone camera for imaging, as opposed to specialized equipment, provided less detailed information, which may have impacted classification accuracy and reliability.

III. METHODOLOGY

A. About the dataset

The study analysed datasets from five rice varieties that are commonly grown in Turkey: Arborio, Basmati, Ipsala, Jasmine, and Karacadag. 75,000 images of rice grains, 15,000 from each variety, make up the image dataset[3]. The training and testing portions of the dataset are divided into two segments: 60,000 images are used for training and 15,000 images are used for testing to evaluate its performance[2]. Then both training and testing data are pre-processed and augumented using ImageDataGenerator. This could include applying various transformations to the images in real-time during training, setting batch sizes for training the models. ImageDataGenerator can help load those batches to the models during training and evaluation. Fig 1 & Fig 2 shows the types of rice data and its distribution used in this research:

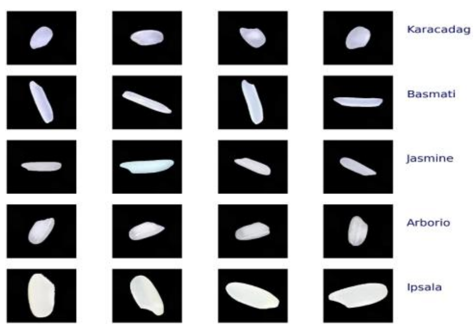

Fig. 1. Type of Rice

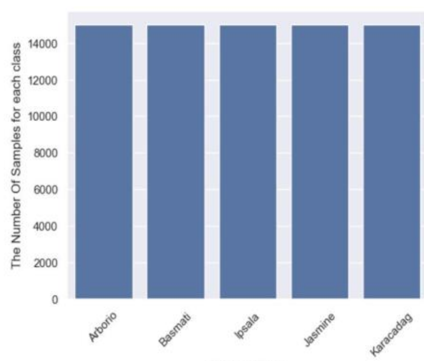

Fig. 2. Distribution of Dataset

B. Model Summary

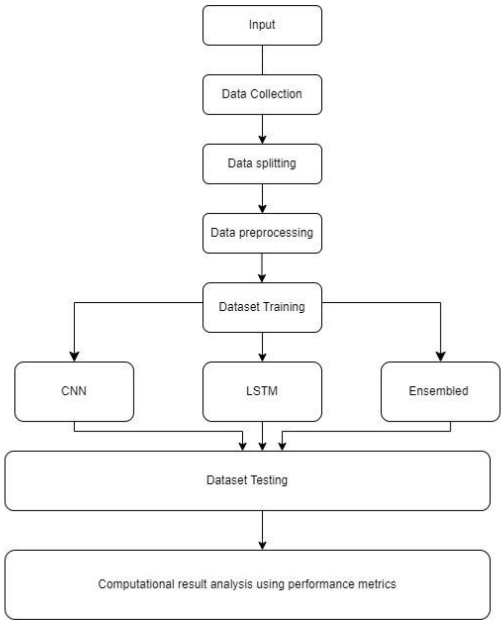

Fig. 3. Flow diagram of proposed models

- *Convolutional Neural Network (CNN)*

Convolutional Neural Network (CNN) have widely been used on image classification, speech recognition, and natural language processing, since they might handle highdimensional data [3]. In this paper, a CNN model is used to classify different rice varieties by analysing their visual traits, such as grain size, shape, and color. In this regard, CNNs are especially useful for image-based classifications; thus, their ability to grasps the spatial hierarchies of images becomes an added plus that makes them really a powerful tool in rice classification.

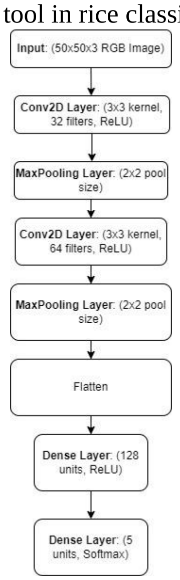

Fig. 4. Architecture of CNN

The CNN architecture has a multilayered feature extraction on the input images. The input image to the model is 50x50x3, passing through the first layer, which is a 2D convolutional layer, Conv2D. This layer applies 32 filters to the input, where each filter is designed to detect different spatial features. Conv2D applies linear filters by sliding the filter over the image doing element-wise multiplications followed by a summation to form a feature map. In that respect, this layer contains 896 learnable parameters, corresponding to a set of weights and biases applied for filtering the image data. Then comes a MaxPooling layer with 32 filters that reduces the dimensionality of feature maps from 48x48x32 to 24x24x32. The process of MaxPooling works by running a window over the top of the feature map and selecting from each region the maximum value. This process helps in retaining important spatial features of the image objects while decreasing computational complexity. This feeds into another Conv2D with a higher number of filters, at 64, and 18496 parameters, strengthening the feature extraction process. Then, it undergoes another MaxPooling layer where 64 filters further reduce the dimensions of the feature maps. Already beyond that, the result gets input to a Flatten layer, which reshapes the 3D feature maps into a 1D vector, thereby preparing it for Fully Connected, or Dense, layers. The first Dense layer has 991,360 parameters and learns nonlinear combinations of the extracted features. Each neuron in a Dense layer is fully connected to all neurons of the layer before it. In this manner, through such complete connections of various neurons, complex boundaries for decisions are built using the activation function:

$$z = \sum_{i=1}^{n} w_i . x_i + b$$

The final classification is done by the last Dense layer with a total of 645 parameters. The architecture is designed in a way that optimizes accuracy by progressive feature extraction, reducing dimensions, and culminating in a final classification according to the learned visual patterns of rice grains.

Layer (type)	Output Shape	Param #
conv2d_16 (Conv2D)	(None, 48, 48, 32)	896
max_pooling2d_16 (MaxPooling2D)	(None, 24, 24, 32)	0
conv2d_17 (Conv2D)	(None, 22, 22, 64)	18,496
max_pooling2d_17 (MaxPooling2D)	(None, 11, 11, 64)	0
flatten_14 (Flatten)	(None, 7744)	0
dense_28 (Dense)	(None, 128)	991,360
dense_29 (Dense)	(None, 5)	645

Total params: 3,034,193 (11.57 MB)
Trainable params: 1,011,397 (3.86 MB)
Non-trainable params: 0 (0.00 B)
Optimizer params: 2,022,796 (7.72 MB)

Fig. 5. Model summary of CNN

- *Long Short-Term Memory (LSTM)*

Long Short-Term Memory Network, LSTM, is a special kind of RNN which can learn the dependencies for a long term. This proves to be really useful in applications like language modelling, time-series forecasting where the information has to be kept for a longer duration of time.

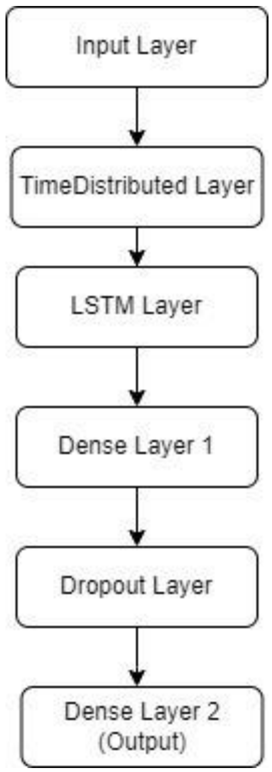

Fig. 6. Architecture of LSTM

This classification can be best served by an architecture capable of capturing long-range dependencies, LSTMs, and maintaining relevant context over time. In utilizing memory cells, it places much emphasis on exact classification through the removal of irrelevant information. The LSTM architecture utilized for this work consists of a number of layers which, when applied, would result in an accurate classification at the end. First is the input layer, which is comprised of 28 time steps at each point, taken with 84 features in length. After that, the input goes to the TimeDistributed layer, which is going to apply the same neural network to every single time step individually. This layer makes sure that the precious patterns of each time step are kept while the data is being prepared for the LSTM layer. In this LSTM layer-which is configured with a size of 128 units and a total of 17408 parameters-the temporal dependencies between the feature vectors across different time steps will be captured. It helps the LSTM produce complex temporal patterns in the rice grain sequence data. The output from the LSTM layer will feed as input into a dense layer with units of 128 to learn nonlinear combinations of the temporal features extracted by the LSTM layer. Then, it is fed to a dropout layer to prevent overfitting and to improve generalization. Finally, the output from the Dropout layer is fed into another Dense layer with 5 units that gives the exact classification for a given rice image.

Layer (type)	Output Shape	Param #
time_distributed_6 (TimeDistributed)	(None, 28, 84)	0
lstm_8 (LSTM)	(None, 128)	109,056
dense_30 (Dense)	(None, 128)	16,512
dropout_10 (Dropout)	(None, 128)	0
dense_31 (Dense)	(None, 5)	645

Total params: 378,641 (1.44 MB)
Trainable params: 126,213 (493.02 KB)
Non-trainable params: 0 (0.00 B)
Optimizer params: 252,428 (986.05 KB)

Fig. 7. Model summary of LSTM

- *CNN & LSTM (Ensembled Learning Model)*

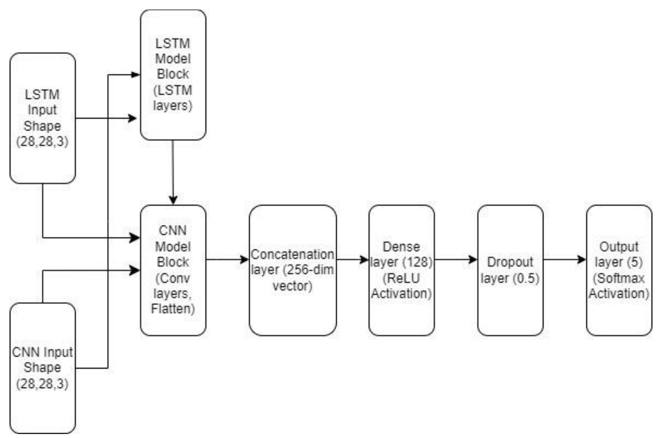

Fig. 8. Architecture of ensemble model

Here, we consider an ensemble approach whereby the outputs of a Convolutional Neural Network and a Long Short-Term Memory network are combined, thereby taking advantage of both models in handling image data and temporal dependencies effectively. The CNN is good at extracting spatial features from image data and effectively captures all the local patterns via convolutional layers. On the other hand, the LSTM has the capability of capturing long-term dependencies and the information in sequences. This will give further insight into the input data with the synergy of the two models. To combine the outputs of both models, we use the concatenate layer to integrate the spatial features learned by the CNN with the temporal features captured by the LSTM. Finally, the combined feature vector is passed through other fully connected dense layers that learn higher-level representations. In order to avoid overfitting and improve generalization, a dropout layer with 0.5

dropout rates was added consecutive to the dense layer. The tile will then be projected to the final output via the softmax activation function, which will ensure that the model outputs a probability distribution over target classes. This ensemble technique may help in improving the whole model performance by learning the spatiotemporal dependencies in the data that a solo CNN or LSTM cannot use. Feature diversity due to the two models is shown to improve multimodal learning performance. Besides this, the method has its added advantage by reducing the variance of the predictions, which will eventually make the model more robust against changes in the input data.

Models	precision					Recall					Accuracy
	Arborio	Basmati	Ipsala	Jasmine	Karacadag	Arborio	Basmati	Ipsala	Jasmine	Karacadag	
CNN	0.96	0.98	0.99	0.96	1.00	0.97	0.99	1.00	0.97	0.97	0.9757
LSTM	0.99	0.95	1.00	0.97	0.98	0.97	0.99	1.00	0.95	0.99	0.9845
Ensemble	0.98	0.98	1.00	0.98	0.99	0.98	0.99	1.00	0.98	0.98	0.9879

Table.1. Performance Metrics of Rice Classification Model

IV. EXPERIMENTAL RESULTS

- Analysis of Performance Metrics

The table. 1 gives the values for precision, recall, and accuracy of three models, CNN, LSTM, and Ensemble, on five rice varieties: Arborio, Basmati, Ipsala, Jasmine, and Karacadag. Among these, the Ensemble model has given more consistent performance with very high ranges of precision (0.98 to 1.00) and recall (0.98 to 1.00) for all rice types, securing a general accuracy of 0.9879. The LSTM model is the most successful at 0.9845, while showing high performance in precision and recall for Ipsala and Karacadag classes with 1.00 and 0.99, respectively. CNN also shows high robust performance but with an overall accuracy of 0.9757, while the models with slightly lower recall can be found for Jasmine and Karacadag (0.97) classes. Overall, the balance between precision and recall of the generalization across rice varieties is higher in the Ensemble model. LSTM has excellent results, especially for Ipsala and Karacadag. Considering CNN, it shows an acceptable performance but with a lower value compared to the other two models.

- Analysis of Accuracy and Loss Comparison

The analysis shows that, after 50 epochs, the LSTM model resulted in an accuracy of about 98% with very minimal overfitting. The training accuracy started at approximately 93%, while the test accuracies began a tad lower. During the first few epochs, the training and test accuracies quickly converged on the value of about 98%. From the 15th epoch onwards, each of these accuracies kept increasing smoothly with few changes. Whereas it stabilized at approximately 98% for both the training and validation set, it demonstrated that there was an effective learning with good generalization across epochs. As for the comparison of losses, the training loss started relatively high and steadily went down to near-zero values in the 20th epoch. The test loss had some fluctuations, especially during the beginning, before it stabilized below 0.05 toward the end. Despite such minor spikes, the convergence of both training loss and test loss was achieved by the model, allowing it to reduce errors with excellent generalization across unseen data. The final results indicated that the LSTM performed strongly, giving very high accuracy and low loss for both training and validation datasets with very little evidence of overfitting at the 50th epoch. These results therefore suggest that the model learned efficiently and was able to preserve good generalization through training. Similarly, the CNN model achieved an accuracy of about 98%, showing very slight overfitting after the 50th epoch. The training accuracy started off at about 88%, and the test accuracy began at about 94%. The early epochs both converged very quickly before sitting smoothly at approximately 98% after the 10th epoch. This behavior means that the model learned well and sustained a high degree of accuracy on the test dataset, as was seen in the training dataset; therefore, it doesn't seem to be much degradation between the two. Concerning the loss, the training loss started at approximately 0.3, going down to nearly zero by the 20th epoch, with a number of fluctuations along the way. The test loss was similar in behavior; after a few spikes in the early stages, it also stabilized quickly around 0.02. Both training and test losses converge, and with minor fluctuation, further verify that the model has generalized well across datasets-performing robustly without overfitting. The final accuracy of around 98% points to the model's strong capacity for generalization combined with an efficient learning process. Finally, an accuracy of around 98% was reached for the ensemble model, without much overfitting after 50 epochs. It started off at an approximate training accuracy of 88% and a test accuracy of about 65%. Both converged very fast in the first few epochs and then stayed at about 98% beyond the 15th epoch, which indicates that the model had attained near-perfect accuracy early in training hence was learning efficiently with minimal overfitting across both datasets. The corresponding loss plot thus shows that in the 10th epoch, the training loss decreased from about 0.5 to almost 0, while the test loss, after a few spikes at the start-once notably over 2.5-quickly converged and went further down to 0.01, eventually flattening with the training loss. This would therefore suggest that, though there was some instability in early training for the model, it did indeed minimize both training and test loss effectively, implying strong generalization and efficient learning. The final results using an ensemble model achieved near-perfect accuracy of 98% on both the training and validation sets, suggesting that this model indeed generalized well with little to no overfitting by at least the 50th epoch.

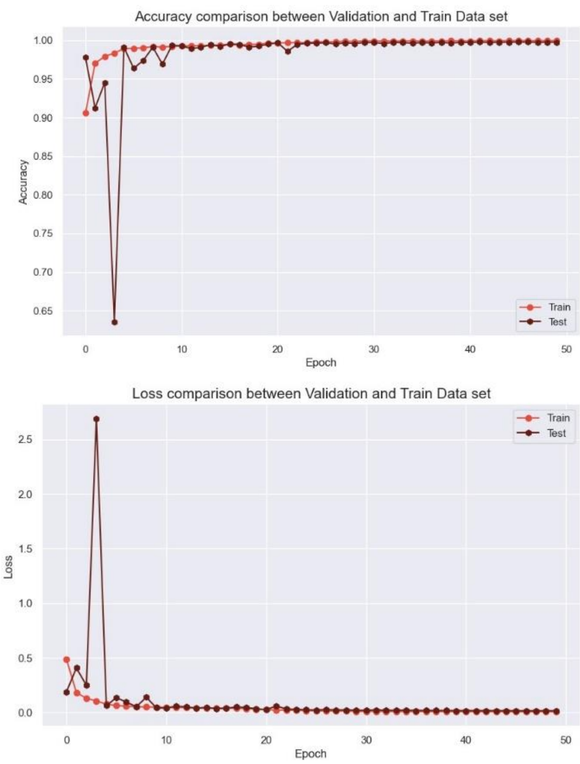

Fig. 9. Accuracy and Loss comparison of ensemble model

- Analysis of Confusion Matrix:

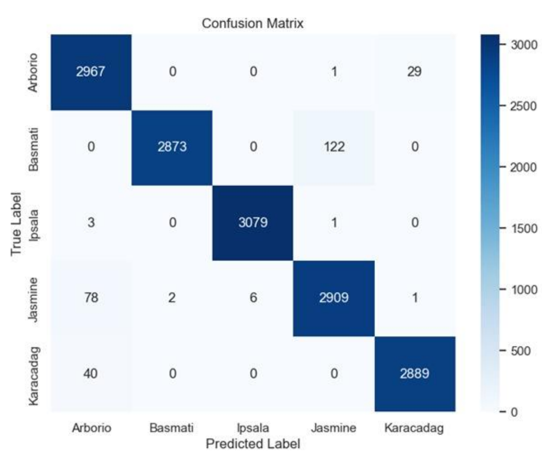

Fig. 10. Confusion matrix of ensemble model

Fig. 10 shows the confusion matrix, showing the performance of a multiclass classification model against the five rice variates: Arborio, Basmati, Ipsala, Jasmine, and Karacadag. It gives the number of correctly classified instances for each class along the diagonal, and misclassified instances are shown in the off-diagonal cells. Actually, the model performs well and the majority of instances are correctly classified: 2,967 out of 2,997 Arborio samples, 2,873 out of 2,995 Basmati samples, 3,079 out of 3,083 Ipsala samples, 2,909 out of 2,996 Jasmine samples, and 2,889 out of 2,929 Karacadag samples. Notable misclassifications include 122 Basmati samples into Ipsala and 78 Jasmine samples into Arborio. Other misclassifications are less marked, such as 40 Karacadag samples which are presently misclassified as Arborio. These errors testify to the poor performance of the model on the distinction among Basmati and Ipsala classes, but also among Jasmine and Arborio classes, due to feature similarities. Though the issues are present, the matrix gives an insight into the performance of the model, thereby showing strengths and weaknesses where better feature engineering or tuning the model parameters would reduce the classification errors.

V. CONCLUSION

This Reseach paper implements rice image classification using deep learning methods. A rice dataset with around 75,000 images of five different rice varieties was chosen. Then the preprocessing of the data was done using Rescaling, Data Augmentation, Flow from DataFrame. Classification of five different types of rice varieties namely, Arborio, Basmati, Ipsala, Jasmine and Karacadag has been done using Convolutional Neural Network (CNN), Long short-term memory (LSTM) and ensemble model. We got an accuracy of 98.25% for CNN, 98.43% for LSTM and 98.6% for ensemble. This model can be further extended for more varieties of rice which clearly indicates the scalability of this model. Additionally, including a user interface to upload the images and classify would greatly help the people making the study even more useful. This work contributes to ongoing attempts to use deep learning for accurate and efficient rice classification.

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