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Dry Fruit Classification Using Deep Convolutional Neural Network Trained with Transfer Learning

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Abstract*—Dry fruits are an important part of daily life and are most consumable in all parts of the Indian continent. It is difficult to identify the quality of dry fruit with the naked eye. Industrialists or consumers consume quality dry fruits that can be evaluated based on their features. Here in this research, a transfer learning-based deep learning model is proposed to classify multiple dry fruits based on the features such as size, shape, and edge. In this study, transfer learning models such as Xception, Inception, VGG16, VGG19 and SqueezNet are used to set weights for the proposed model and the model is trained with these weights and the dry-fruits dataset. The most appropriate features of dry fruits have been extracted using a fully connected network and combined with transfer learning weight to classify dry fruits. The proposed model was trained and tested with dry fruit images taken from a dataset containing four classes of dry fruits. The proposed model attained a classification accuracy of 98.53%. The model is compared with other deep learning models and the proposed model outperforms.

Keywords— pre-trained neural network, deep neural network, image processing, segmentation, innovation, classification Ecosystems

I. INTRODUCTION

Agriculture is the backbone of the Indian economy that depends on the quality of produce from the agriculture sectors. The quality of agricultural produce is checked on various parameters before export. In the past few years, the Indian export market of agriculture products has increased up to $49 billion and reached to sixth largest exported [1]. India has a huge market for dry fruits and exports dry fruits to other countries. In the dry fruit export market, India is the second largest producer of the same. Dry fruits are used for many purposes such as to prepare sweets and medicines etc. Dried fruits are used in medicine due to the presence of a sufficient number of nutrient values. But dry fruits are so expensive and in most cases, it is difficult to identify the quality product with the naked eye [2]. Thus, an efficient technique is required to identify the quality of dry fruits using computer vision technology. Dry fruits may be categorized in several ways depending on their size, color, and form.

In this work, the emphasis is to classify dry fruits based on morphological features using a transfer learning-based deep neural network[3][4]. In the proposal, the pre-trained model's predefined weights are used to classify dry fruits images. The proposed technique is better in terms of performance and reliability. In this study, four categories of dry fruits have been used for classification.

A. Transfer learning

Transfer learning improves learning in a new task by transferring information from a comparable task that has previously been learned. Humans may share information between people and tasks. They may use their prior problem-solving experience for new ones. The transfer is easier when the new challenge is similar to previous learning experiences. Machine Learning (ML) learners may share knowledge. Experts in a relevant subject who have solved similar difficulties are better at addressing new challenges than others. Thus, initializing an ML training is like training an expert. Transfer learning involves teaching a new topic to a student with associated previous information. Transfer learning has several successes in the ML sector, such as improving computer vision by using earlier models trained on massive picture datasets like ImageNet.

Transfer learning may also solve materials science's little data challenge. Themes with cheaper experiments or a lengthy history of study often have more data measurements than innovative or costly topics. Inhomogeneous and limited training data cause ML models to extrapolate. One attribute or class of material with little data may be physically connected to another with more data. Transfer learning may help ML models extrapolate. A source-task knowledge model may be trained on a property or substance using plenty of data. An ML strategy applied to a limited collection of data for a related property might leverage the trained model.

B. Neural Networks for transfer learning

Neural networks may transfer learning. Neural networks have several layers linked sequentially. Neurons form each layer. The input layer feeds one neuron per data point feature. Each feature's value is multiplied by weight to signal the following layer's neurons. Each neuron activates this signal to output. Artificial neuron "activation functions" are mathematical functions between input and output. Each neuron transforms signals nonlinearly. By layering artificial

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neurons, characteristics may be abstracted. Neural networks learn complex patterns and interactions using non-linear activation functions. The second layer receives the first layer's outputs in various ways depending on the network's design. Fully linked or dense layers connect all neurons in the input layer to all neurons in the output layer[5][6].

The research focuses on dry fruit categorization using convolutional neural networks trained using deep learning.

C. Organisation of Paper

The remaining portions of the paper are organized as follows: Section II provides context for this study by discussing relevant prior research; Section III describes the resources and approach used; Section IV analyzes the experimental data; and Section V provides an interpretation of the study's findings.

II. LITERATURE REVIEW

Various artificial intelligence-based techniques and methods have been implemented to classify dry fruit based on the image dataset. Deep learning technology has been used in the binary classification of various types of dry fruits.

A novel machine-learning method has been discussed in [3] to classify whole and split cashew. Here in this study, the idea of grayscale intensity is used to identify split and whole cashew nuts. This technique attained an accuracy of 100%.

In [4], a supervised learning approach has been used to classify almonds based on morphological character. In this paper, two classification techniques Support Vector Machine(SVM) and an Artificial Neural Network(ANN) have been employed to classify almond nuts. Feature vector has been defined based on the feature selection with principal component analysis. The technique attained maximum classification accuracy.

Computer vision techniques using a convolutional neural network have been employed to classify cashew nuts based on morphological characters [7].

In [8], an image-based deep learning system was developed to classify date fruit based on quality features. Here in this paper, a VGG-16 architecture was used to classify dates based on the size of the dates. The model was trained on an image dataset and attained an accuracy of 96.80%

A convolutional deep neural network was trained with 2866 images to classify nuts and attained 98% accuracy[9].

Fruit classification and grading techniques were employed in [10] using soft computing techniques. Here robust feature was extracted using Speeded Up Robust Features, Histogram of Oriented Gradient, and Local Binary Pattern based on morphological characters such as shape and size. In [11] 13-layer deep neural network was used to classify fruits based on the image dataset. Here 173 fruit image dataset was used to train and test deep neural network and attained 94.94%.

The emphasis of this work is multiclass classification and proposed a transfer learning-based deep neural network to classify various types of dry fruits. In this work, the pre-trained model weights are combined with a fully connected neural network to classify dry fruits.

III. MATERIAL AND METHODS

A. Datasets

The dry Fruits dataset[12] with four different classes has been used in this study.

A total of 800 photos representing 4 types of Dry fruits were included in the gathered dataset. The dry fruit dataset example is shown in Fig. 1.

Each of the four types of dried fruits—Apricot, Almond, Cashew, and Date—has its picture bank with 200 options. A total of 85 percent of the data was used to create the Train Image Set, while 15 percent was used to create the Test Image Set.

Fig. 1. Dry Fruit Dataset samples

B. Methodology

Fig. 1 depicts the general approach that will be used in the proposed research.

The methodology steps are:

1. Image argumentation and pre-processing
2. Image Segmentation
3. Transfer Learning Models

1) Image Pre-Processing and Argumentation

This is an initial level that covers three different classes of operations such as argumentation, pre-processing, and segmentation.

- The argumentation is used to enhance the dataset using various types of operations such as flipping, rotation, shifting, and nosing.
- After dataset enhancement, pre-processing is employed to enhance image quality. A better outcome can be achieved by analyzing network structure and datasets. Thereafter, the image features are extracted to predict accuracy. In this stage of processing, we first scale all of the images to the specified 256 pixels by 256 pixels. Python library functions are used to carry out the same operation as precisely as possible.

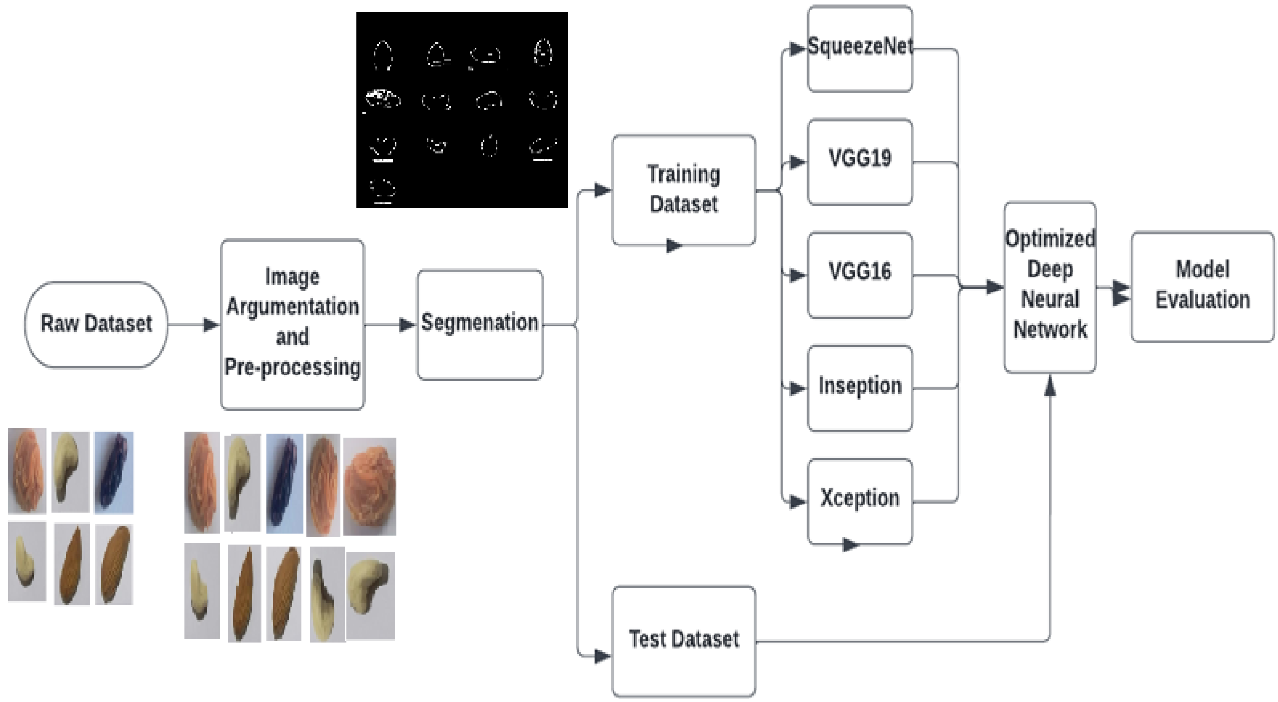

Fig. 2. Proposed Methodology

2) *Segmentation*

Vegetation segmentation is the last step, and it involves breaking the picture into tiles and then using those tiles to extract the area of interest that has the illness.

3) *Transfer learning models based on Optimized Deep Neural Network*

The objective of pre-trained models is to extract features from the dataset and transfer weights to networks[13]. Various types of transfer learning models are used in the research to transfer knowledge as given below in Fig. 3:

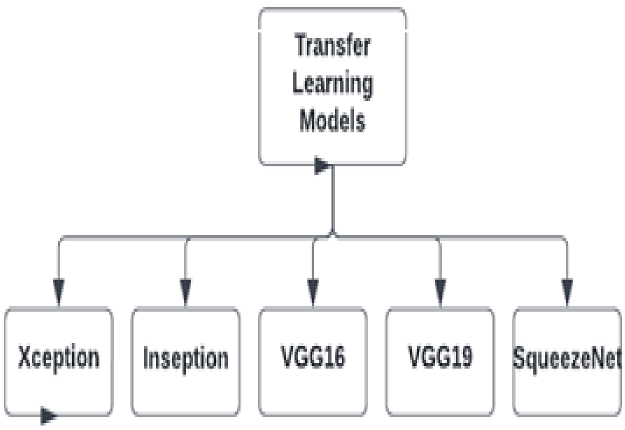

Fig. 3. Transfer Learning models

Here, CNN is the most useable network that is used to categorize pistachio images.

4) *Performance Metrics*

ACC: Accuracy, AUC: Area Under Curve, PRE: precision, F1: F1- Score, and REC: Recall performance metrics are used to evaluate the models.

IV. Results and Discussion

The whole experiment was coded in Python and managed in Co-Lab. The experiment is run with several different training-testing ratio configurations, including 70:30 with cross-fold validation of 5, 10, 15, and 20, and the average classification validation accuracy is reported for each arrangement.

A. Analysis using Sampling

To determine the extent to which quantity epochs impact system performance, tests are conducted. The experiments are run with varying epoch values (50, 100, 200) and leaning rates (0.1, 0.01, 0.001, 0.0001). Fig. 4-7 shows the results on Training/validation accuracy and loss of the proposed Xception model at epoch values 50,100, 150 and 200 with a learning rate (LR) 0.001.

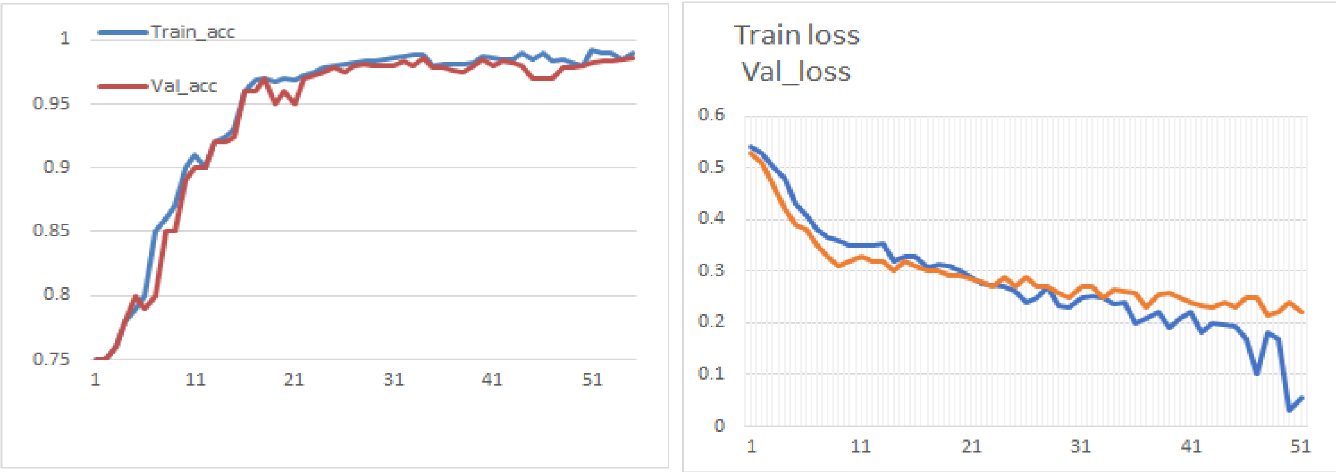

Fig. 4. Training/ Validation Accuracy and loss with LR 0.001 and 50 epochs

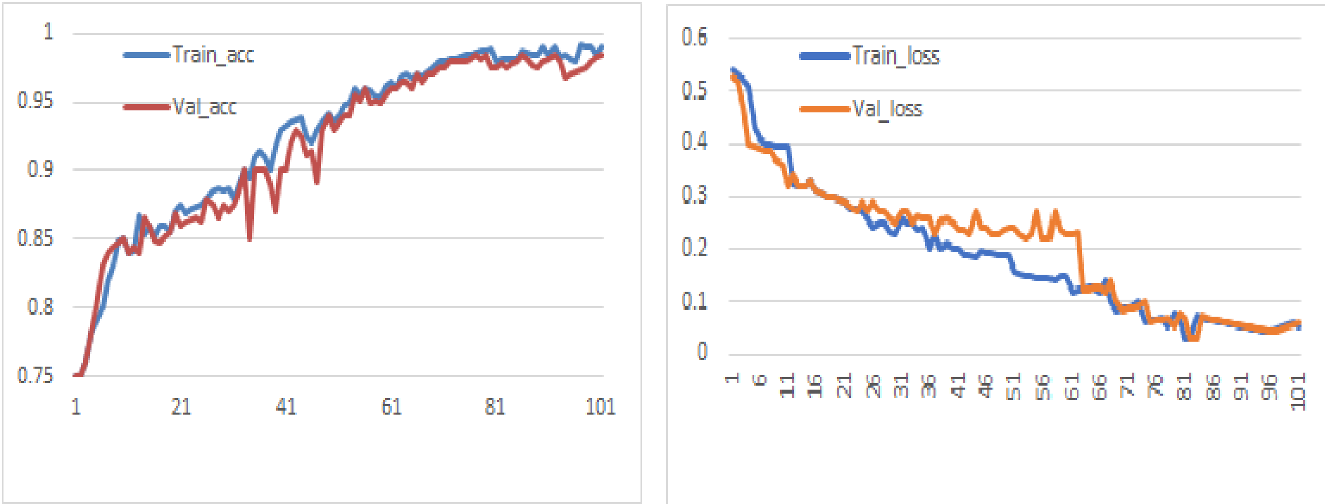

Fig. 5. Training/ Validation Accuracy and loss with LR 0.001 and 100 epochs

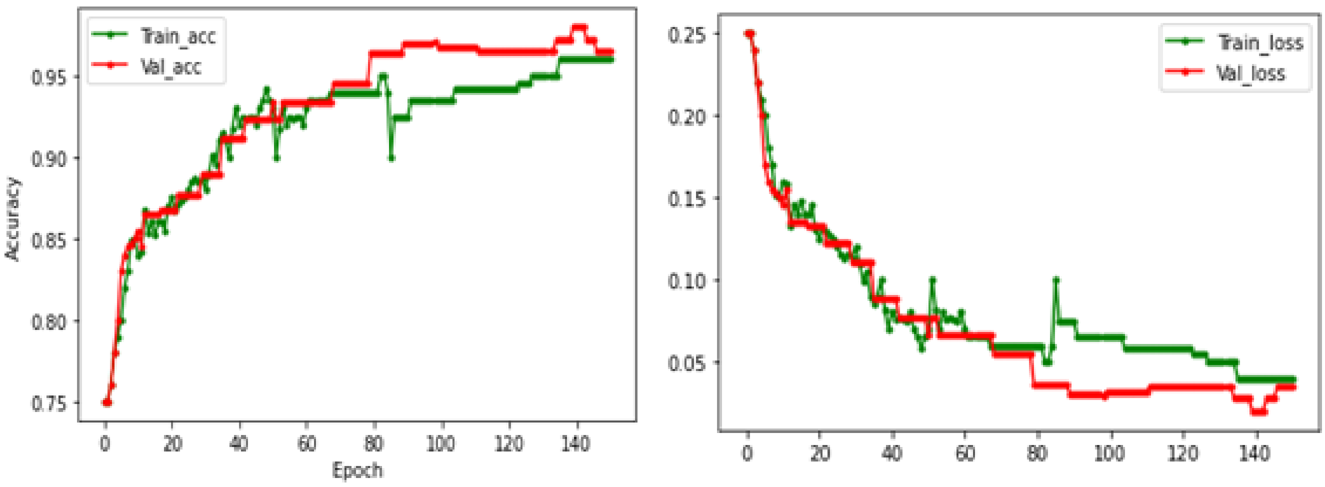

Fig. 6. Training/ Validation Accuracy and loss with LR 0.001 and 150 epochs

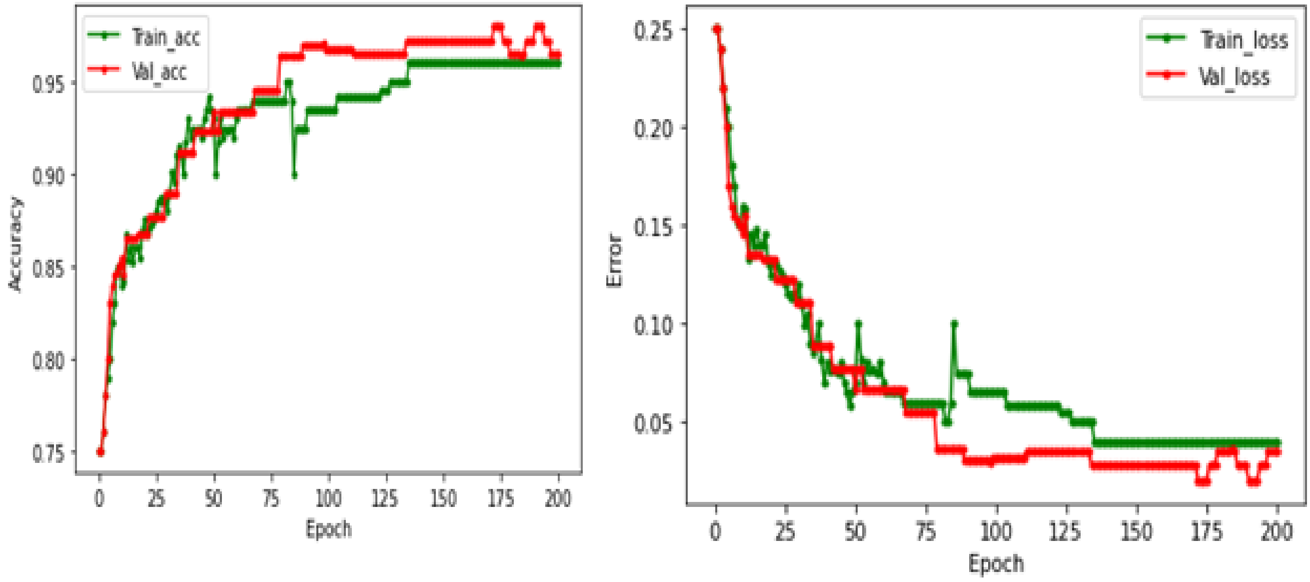

Fig. 7. Training/ Validation Accuracy and loss with LR 0.001 and 200 epochs.

B. Analysis using Cross Validation

The experiment is performed with different cross-validation values such 5,10 and 20. The best results were obtained with proposed Squeezenet and Xception deep networks models with 20 cross-validations as shown in table I-II and fig. 8-9.

TABLE I. RESULT WITH SQUEEZENET

MODEL	AUC	ACC	F1	PRE	REC
kNN	0.93714112	0.872439	0.872922	0.875264	0.872439
SVM	0.988380717	0.958101	0.958129	0.9582	0.958101
Random Forest	0.944569486	0.883147	0.882278	0.884158	0.883147
Proposed Model	0.992039961	0.98536	0.98536	0.98536	0.98536

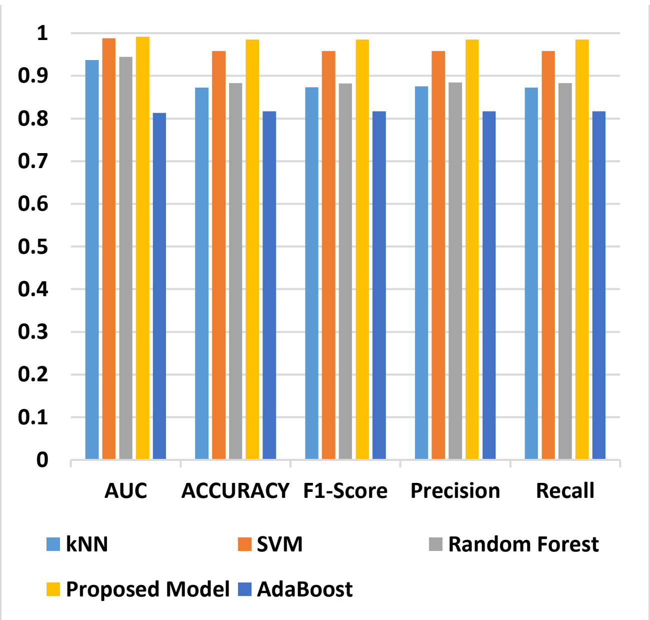

Fig. 8. Proposed Model with SqueezeNet

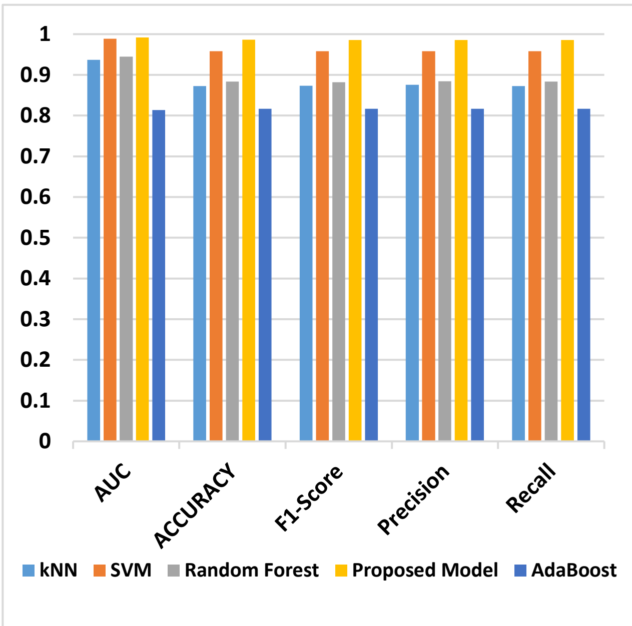

Fig. 9. Proposed Model with Xception

TABLE II. RESULT WITH XCEPTION

MODEL	AUC	ACC	F1	PRE	REC
kNN	0.9371411	0.872439	0.872922	0.875264	0.872439
SVM	0.9883807	0.958101	0.958129	0.9582	0.958101
Random Forest	0.9445695	0.883147	0.882278	0.884158	0.883147
Proposed Model	0.99204	98.63%	0.98536	0.98536	0.98536

V. CONCLUSION

In this paper a transfer learning-based deep neural network was proposed to classify multiple dry fruits. Here the image morphological features are deeply extracted using a fully connected neural network and weights of the pre-trained models used to classify dry fruits. Deep learning model Xception gives the best results (98.63% accuracy) with 20-fold cross-validation. The results show reveal that this model is adequate to simulate dry fruit recognition. The limitation of this study is the number of dry fruit classes that can be enhanced in future work. Additional regionally-specific Dry fruit types will be added to this project in the future.

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