CLASSIFICATION OF FRUITS USING CONVOLUTIONAL NEURAL NETWORK AND TRANSFER LEARNING MODELS

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ABSTRACT

Automated categorization of freshness of fruits plays pivotal role in the agricultural industry. In conventional method, the grading of fruit is assessed by human being. This method is cumbersome, inconsistent and easily influenced by surrounding. Therefore a fast, accurate and automated system is required for the industrial applications. The current work uses a deep learning based model for classification of fruit freshness. Proposed Convolution Neural Network (CNN) model is implemented by using public dataset named as "fruit fresh and rotten for classification" derived from kaggle. Using the dataset, three varieties of fresh fruits (Apple, Banana, and Oranges) and their rotten category are used for experiment. A deep learning based CNN model is used to extract the characteristics or attributes from the available fruit images. A softmax function then takes the input images and segregates them into fresh and rotten category. Proposed CNN model evaluates the dataset efficiently and gives the accuracy of 98.23%. Results shows that our proposed CNN model is working efficiently in classification of fruits. In current work four Transfer Learning methods are also investigated for classification of fruits. Classification performance comparison proves that Convolutional Neural Network model is more efficient than the transfer learning models.

Keywords: CNN, Agriculture, Transfer-Learning models

INTRODUCTION

India is one of the largest fruit producing countries. Identifying defected fruits and classifying fruits in "fresh" or "rotten" category poses a major problems in Indian agricultural sector. Since it is difficult in the industry to classify fruit quality by conventional methods, new technology based on image processing is required for classification of fruits (D. Karakaya et.al, 2019). It is essential for assessing produce, meeting quality standards and increasing market value. It is also useful for planning, packaging and marketing (Jana & Parekh, 2017). Human-made manual assessment are error-prone, inconsistent and time consuming. Machine Vision system can be used to perform automatic classification. This helps to avoid the problems associated with traditional categorization. Recent advances in Deep Learning, particularly in the field of Computer Vision, have improved categorization efficiency. This method is more efficient, error-free, and allows for automated image-based inspection analysis. Image categorization methods based on machine vision are becoming increasingly prevalent.

LITERATURE REVIEW

Generally the ML approach is extracting the image feature-metrics for the classification. This includes various processing steps such as image preprocessing, feature extraction, classification model development, and validation (Jana et.al.,2017; Hou et.al.,2016;

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Azizah,2017; Thenmozhi et.al.,2019). Much work related to fruit classification has been put forward. Support Vector Machines (SVM) display acceptable results on small data sets. This can be done flawlessly using deep learning based defined neural networks (Saranya et.al., 2020).

CNN based model improves image classification for large datasets. The CNN based model (Palakodati et.al., 2020) has achieved accuracy of 97.82% in classifying fresh and rotten category of fruits. Three Convolution layers, three Max pooling, one fully connected layer, and a softmax classifier were used to achieve the mentioned accuracy in 225 epochs. In comparison to a few transfer learning models, this model performed better.

The fruit recognition rate was evaluated using only CNN and CNN with a selective algorithm (Hou et.al.,2016).CNN with optional algorithm is proven better than when used CNN alone. Although efficient recognition rate is achieved but work has been done on small classes of fruits and changes in the external environment and other factors such as light are not taken into account in creation of database.

The CNN model (Azizah et.al.,2017)was used for detecting the defect on mangosteen with accuracy of 97%. Before applying CNN for classification experts manually perform sorting of mangosteen. Image classification by CNN includes 4-fold cross validation process.

Fungus detection and discrimination between various kinds of fungus is done by CNN architecture with 11 layers (Tahir et.al.,2018). CNN layers includes 3 convolution, 3 ReLU, 3 pooling and 2 fully connected layers. Accuracy of 94.8% is achieved with 5-fold validation. Fine tuning between different parameters has been done for better results.

Crop insect classification is a big challenge (Thenmozhi et al., 2019), and to solve it, deep CNN models were employed on NBAIR, Xie1 and Xie2 datasets. With the NBAIR, Xie1 and Xie2 datasets, accuracy in insect categorization was 96.75 percent, 97.47 percent, and 95.97 percent, respectively. With the same datasets, several transfer learning models (AlexNet, ResNet-50, ResNet-101, VGG-16, and VGG-19) were employed in insect classification. When compared to the transfer learning model, the CNN model was shown to be more efficient in this study.

CNN is frequently employed in the area of agriculture for picture categorization of a variety of issues (Kamilaris et.al.,2018). The current study shows that a CNN model based on deep learning is more effective in classifying fruits as "fresh" or "rotten." The suggested model's accuracy is also compared to that of other transfer learning methods. Six classes were created from three different varieties of fruit. That is, each fruit is classified as either fresh or rotten. The VGG16, VGG19, AlexNet, and LeNet-5 transfer learning models are investigated. When compared to existing defined models, our system displays a robust CNN model that has enhanced the accuracy for fresh and rotten fruit classification. For better outcomes, we additionally look at the impact of other hyper parameters.

MATERIAL AND METHODOLOGY

Dataset

The current work uses dataset “Fruits fresh and rotten for classification” in fruit classification process. This data set is acquired from Kaggle and has been engineered by collecting, separating, and then labelled. This dataset includes 10,901 images of three types of fruit with six classes of fresh fruit and rotten fruit. The size of training, validation and test sets are 5451, 2180 and 3270 respectively. Figure 1 shows the sample images of three fresh and three rotten fruits from the datasets.

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FIGURE 1:

EXAMPLE OF IMAGES IN DATASET (1 FRESH APPLE, 2 FRESH BANANA, 3 FRESH ORANGE, 4 ROTTEN APPLE, 5 ROTTEN BANANA, 6 ROTTEN ORANGE)

Convolutional Neural Network

Convolution neural networks (CNN) are today's most popular class of models for image recognition and classification. One of the big advantages of using CNN is that it requires much less preprocessing time as compared with other classification algorithm. To improve the classification process it processes the input data, gives training to model and then takeout the important information automatically. The primary purpose of a CNN algorithm is to download data in a managed format without losing important features in understanding what the data represents. This makes it suitable for working with large data sets. CNN is composed of mainly three layers. The number of layers varies depending on complexity of the problem domain. In complex applications, the number of such layers increases significantly. The image goes through these series of layers, first is convolutional layer, next is pooling layer and finally fully connected layer. After that it generates the output.

In convolution layer filters are applied to the original image. It extracts features from the image. Most of the user-specified parameters i.e, numbers of kernels and size of the kernel are found in the convolution layer. Max pooling or average pooling is performed via pooling layers. In most pooling layers, the maximum pool technique is employed. They're often employed to shrink the size of a network. The completely linked layers are the network's final layers. The output from the previous pool or convolution layer is used as the input for this layer. It classifies the input image into distinct labelled classes using the softmax activation function. Figure 2 represents Basic composition of CNN.

FIGURE 2:

BASIC CNN STRUCTURE FOR CLASSIFICATION

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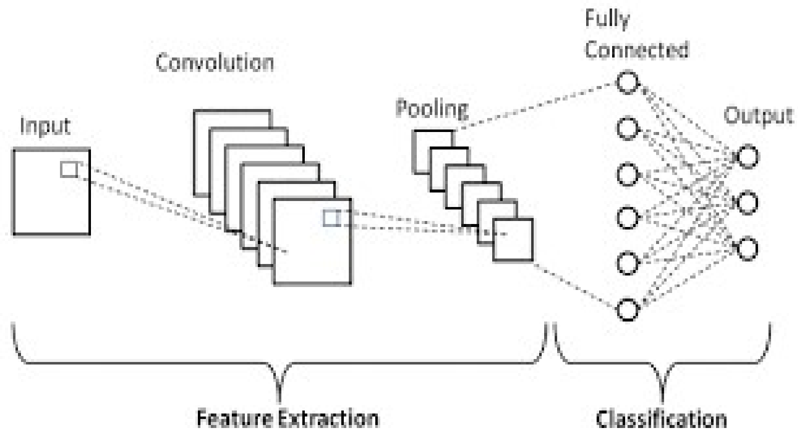


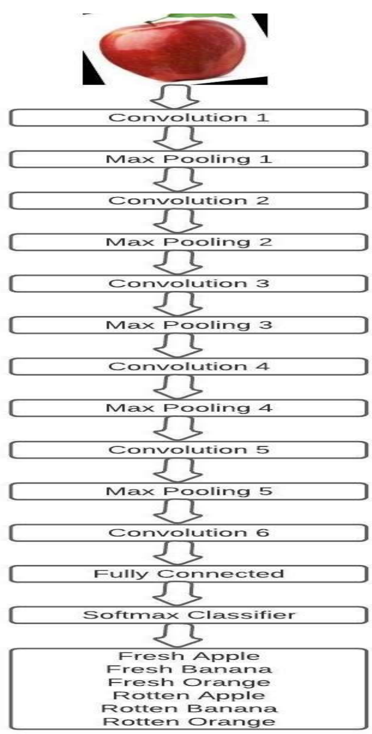
Proposed CNN based model

The current study proposes a deep learning-based CNN model for identifying fresh and rotten fruits. This model is made up of the following layers (i) Six convolutional layers (ii) Five max pooling layers (iii) Two fully connected layers (iv) Softmax classifier output layer.

The fruit dataset is initiated with an input image size of 224 × 224. First convolution layer (Convolution 1) layer contains the activation function of the Rectified linear unit (ReLU). It aids the model in learning quicker and performing better. From convolution layer 1 through convolution layer 5, a combination of convolution and max pool layer is employed. After each convolution layer, a max pooling layer with a size of 2 x 2 and a stride of 2 is applied. Number of filters used and kernel size at all layers are mentioned in table 1. Convolution layer 6 uses 256 filters with kernel size of 3.

FIGURE 3:

PROPOSED LAYOUT OF MODEL CNN



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Finally, the fully connected layer is used as dense layer. Flatten layer was implemented before using the dense layer in order to flatten the feature map and a dropout layer was added after the flatten layer. The results of the classification are fed into the softmax classifier layer as input. The present model uses a categorical cross-entropy loss function and an Adam optimizer with a learning rate of 0.0001. Figure 3 depicts the suggested CNN-based model's layout. Table 1 lists the layers utilized in the present project.

TABLE 1
DESCRIPTION OF LAYERS CURRENTLY IN USE

Layers	Size of the output	Size of the Kernel	Stride
Input Image	224 x 224	-	-
Convolution 1	220×220×8	5	1
Max Pooling 1	110×110×8	2	2
Convolution 2	106×106×16	5	1
Max Pooling 2	53×53×16	2	2
Convolution 3	47×47×32	7	1
Max Pooling 3	23×23×32	2	2
Convolution 4	21×21×64	3	1
Max Pooling 4	10×10×64	2	2
Convolution 5	8×8×128	3	1
Max Pooling 5	4×4×128	2	2
Convolution 6	2×2×256	3	1
Flatten	1024		
Dense	512		
Softmax	6		

Transfer Learning models

In deep learning, transfer learning is a technique for training neural network models for problems similar to those being solved. Transitional learning has the advantage of reducing the training time of the training model and may reduce generalization. The current work includes performance comparisons of CNN model with LeNet-5, Vgg-16, Vgg-19 and AlexNet models.

Alexnet

AlexNet is a Convolutional Neural Network designed by AlexNet (Krizhevsky et.al., 2012). It is included because it is the most thoroughly researched CNN and provides a reasonable balance of speed and accuracy. It is made up of eight layers that are all weighted (five are Convolutional Layers and three are Fully Connected Layers). Weights are applied to all eight layers. It uses data augmentation and dropout to reduce overfitting. This model requires a 227 X 227 X 3 input picture. The ReLU function is employed after each convolution and fully linked layer to improve the model's non-linear features. The final fully connected

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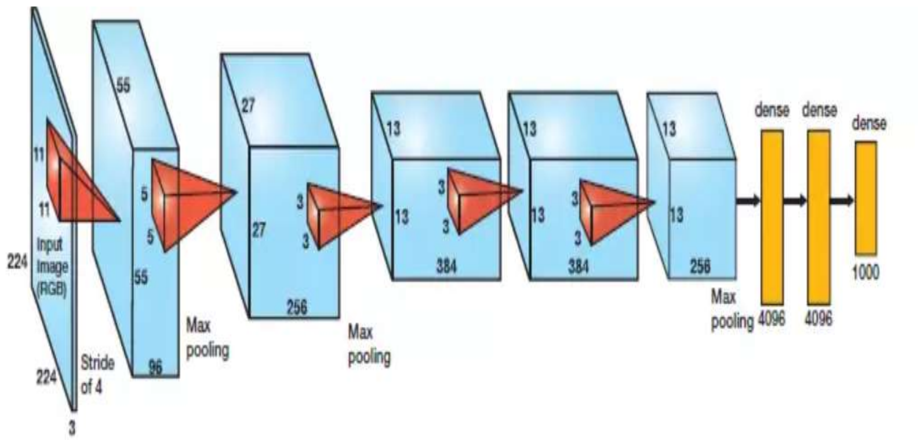
layer, which is supplied to the softmax function as input, consists of 1000 neurons that are utilised to categorise 1000 classes. AlexNet's fundamental design is seen in Figure 4.

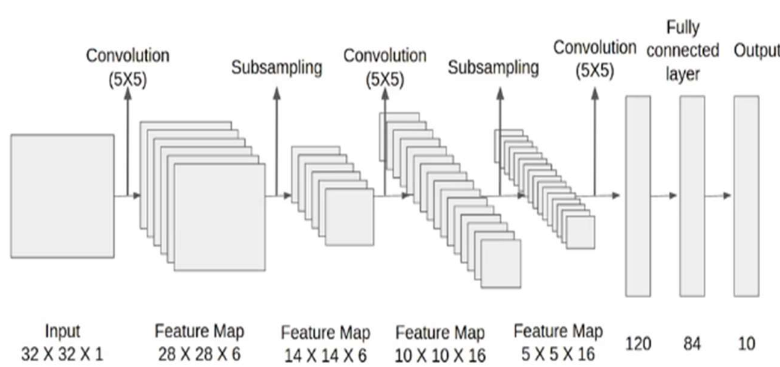
FIGURE 4:
BASIC ARCHITECTURE OF ALEXNET



LeNet-5

Lenet-5 is one of the earliest pre-trained models suggested by Yann LeCun et.al in the year 1998 (Lecun et.al., 1998). The main reason for the popularity of this model is its simple architecture. This is a multi-layer Convolution neural network for image classification. This network consists of seven layers out of which five layers are with trainable parameters and therefore it was called Lenet-5. Three convolutional layers, two subsampling layers, and two fully linked layers with softmax classifiers make up this algorithm. This model employs average pooling in the subsampling layer. The size of the filters in each convolution layer is quite tiny, i.e. 3 3. Some, but not all, of the convolution layers are followed by 2X 2 max pooling layers. The fundamental structure of Lenet-5 is shown in Figure 5.

FIGURE 5:
BASIC ARCHITECTURE OF LENET-5 ARCHITECTURE



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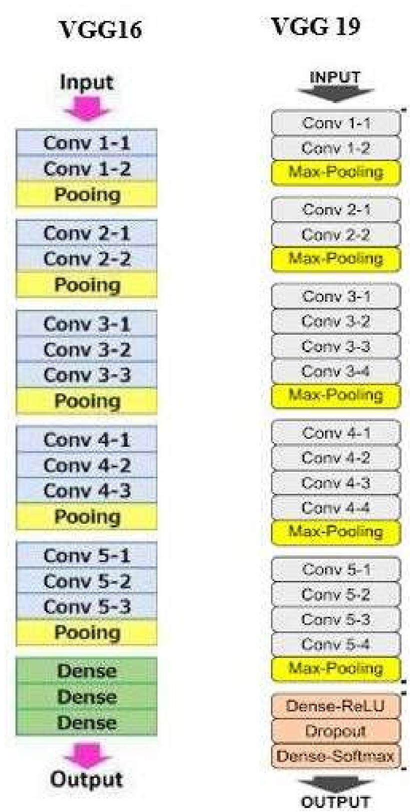
VGG Net

The VGG model was developed by Simonyan and Zisserman in 2014 (Simonyan & Zisserman, 2014). Authors have explored that depth is one of the important aspect of Convolution neural network architecture design. Both VGG architecture has different depths (number of layers). Depth of VGG decides its nomenclature. VGG 16 is the name for 16 layers, while VGG 19 is the name for 19 layers. The architecture of VGG16 and VGG19 is shown in Figure 6. The VGG network is based on the concept of a deep network with tiny filters. This model composed of many convolutional layers (depends on architecture), five max pool layers, three fully connected layer and a softmax layer.

FIGURE 6:
VGG-16 AND VGG-19 ARCHITECTURE



RESULTS

The present work includes testing of fresh and rotten category of fruits. Dataset utilized in this study is “fruits fresh and rotten for classification”. Firstly, the dataset is partitioned into three categories. 50% dataset has used in training while the remaining 20% in validation and 30% used for testing. Validation and training of the same is done simultaneously. In the training process impact of various hyper parameters (mentioned in discussion section) were analyzed and adjusted to get a precise model as compared with pre-trained transfer learning models. We used a Google colab with an HP Z2 MT with a Core i7-8700, 8 GB RAM, 1 TB HDD, and NVIDIA P400 graphic card to run this deep CNN-based model.

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DISCUSSION

CNN Model Parameters Proposed

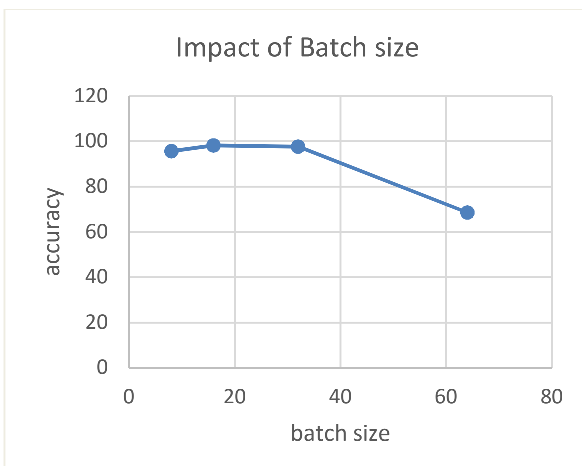
The Adam optimizer is used to train the model, which has learning rates of 0.1, 0.01, 0.001, and 0.0001.Batch size of 8, 16, 32 and 64 is used and the maximum number of epochs varies up to 25. The model is trained with a training set of fresh and rotten fruit and accuracy evaluation is done by using the test set.

IMPACT OF HYPER-PARAMETERS OF THE MODEL

1) Batch Size

Accuracy of classification model is affected by the specification of batch size. Bigger batches takes more training time, it also influence the memory requirement and overall performance. Therefore, appropriate batch size selection is must to improve the quality of model. Batch sizes of 8,16,32,64 is evaluated in current study. As the batch size grows from 8 to 16, the model's accuracy improves. It drops to 32 and then drops by 64 more times. Figure 7 indicates that the model performed best with a batch size of 16 people.

FIGURE 7:
IMPACT OF BATCH SIZE



2) Number of Epochs

The number of runs over the complete training dataset is represented by epochs. The proposed model is trained over a period of 25 epochs. The model is trained at different numbers of epochs 5, 15, 20, and 25 after selecting the batch size 16, learning rate 0.0001, and Adam optimizer. In 25 epochs, a classification accuracy of 98.23% is achieved. The influence of the number of epochs is seen in Figure 8.

FIGURE 8:
IMPACT OF EPOCHS

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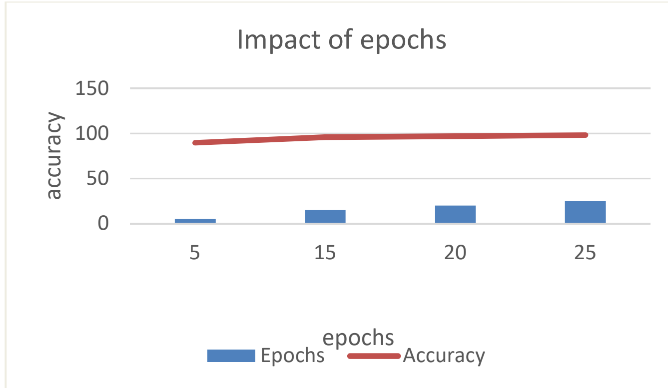
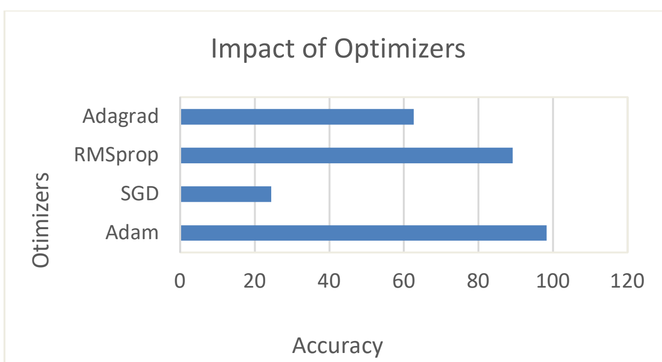


3) Optimizers

Another important factor is to choose optimizer which optimizes model's performance. It reduces the loss function by updating the weight parameter. By changing the network's parameters, our objective is to reduce the loss of neural networks. The neural network loss function is assessed by comparing the real and predicted values. Assessment of four optimizers and accuracy comparison is done to figure out the best optimizer. Four optimizers used in presented work are stochastic gradient descent (SGD), Adam, Adagrad, and RMSprop. Based on analysis best optimizer is found to be Adam optimizer which gives the accuracy of 98.23% where as RMSprop , SGD and Adagrad gives the accuracy of 89.19 %, 24.43% and 62.65% respectively. Figure 9 shows the impact of different optimizers.

FIGURE 9:
IMPACT OF OPTIMIZERS



4) Learning Rates

A certain amount of weights are updated during training with neural networks. This is referred to as the learning rate. The learning rate has a significant impact on the performance of CNN models. It can range between 0.0 and 1.0. We used four different learning rates to train our model and saw how they affected accuracy. 0.1, 0.01, 0.001, and 0.0001 are the four learning rates utilized in this study. Based on analysis we found that the training accuracy improves from 19.97% to 98.23% if the learning rate is reduced from 0.1 to 0.0001.figure 10 shows the impact of learning rates.

FIGURE 10:
IMPACT OF LEARNING RATE

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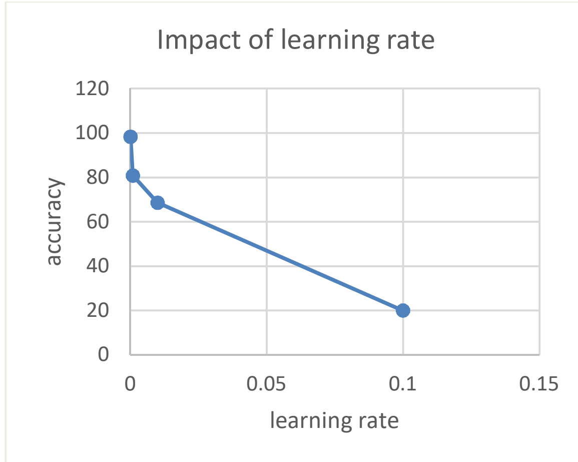
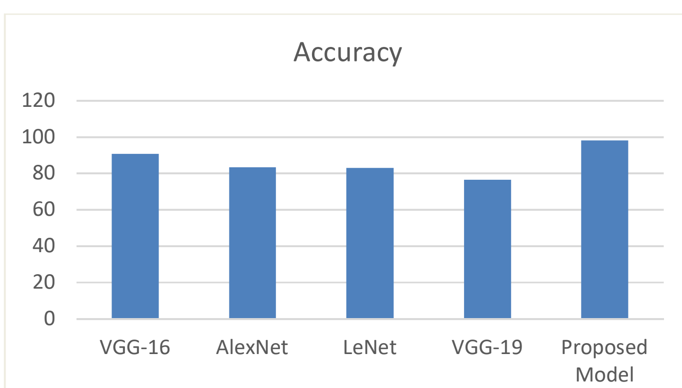


EVALUATION OF SUGGESTED MODEL'S CLASSIFICATION ACCURACY AND TRANSFER LEARNING MODELS

Hyper-tuning of parameters during the training phase yielded the best combination of hyper parameters. Batch size-16, number of epochs-25, optimizer-Adam, and learning-rate-0.0001 are the best combinations. After configuring all of these hyper parameters, testing was conducted on the test dataset, yielding an accuracy of 98.23%. VGG16 outperforms all other transfer learning models in terms of accuracy, with a score of 90.81 percent. Because there are fewer filters and parameters in the proposed model, it takes less time to compute and uses less memory. As a result, it may be used to distinguish between fresh and rotten fruits. Because of the combination of convolution and pooling layers, as well as precise adjustment of hyper parameters, the suggested CNN model has the greatest accuracy (98.23%). To enhance training while minimizing overfitting, the RELU activation function is employed between the convolution and max pool layers. The dropout value is 0.5. The error loss is reduced using Adam's optimizer. Figure 11 depicts a comparison between the suggested technique and the pre-trained model's performance. The results show that the suggested approach is more efficient than the current transfer learning model.

FIGURE 11:
A COMPARATIVE STUDY OF ACCURACIES OF THE PROPOSED METHOD AND OF THE PRE-TRAINED MODELS



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The accuracies of suggested and transfer learning models are compared in Table 2.

TABLE 2
COMPARISON OF THE ACCURACIES

Model	Accuracy
VGG-16	90.81
VGG-19	76.48
LeNet-5	82.93
AlexNet	83.56
Proposed Model	**98.23**

CONCLUSION

The auto categorization of fruit in fresh and rotten category is demanding as well as important task in agriculture industry. The current study compares the performance of a CNN-based model with a pre-trained transfer learning model for fruit categorization. AlexNet, LeNet-5, VGG-16, and VGG-19 are the transfer learning models utilized in this study. The suggested model is compared to the performance of existing models, and the influence of various hyper parameters is investigated. The results of the comparisons reveal that the proposed CNN model's classification accuracy is better and more robust than transfer learning approaches in the categorization of fruits. The accuracy of 98.23 % is achieved in proposed CNN model. Accuracy of proposed model and transfer learning model is shown in the table 2. Manual method of classification is error prone and time consuming. With the help of proposed model these problem can be reduced.

FUTURE SCOPE

Future work includes an automated system with a large number of fruit classes can be designed so that it will be beneficial for all fruit farmers and developing a mobile application that takes images of fruits and classify them in fresh and rotten accordingly.

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