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Rice Disease Classification using Deep Convolutional Neural Network

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Abstract: ***For an Agro-based country like India where agriculture acts as a main source of livelihood for more than 50% of the population, crop diseases are a major threat to food security. Hence, digital image processing along with proper machine learning algorithms can be utilized for the classification of diseases from the images of a plant. In this paper, a comparative study on the effects of different machine learning models on crop disease prediction has been done. Since Convolutional Neural Network (CNN) proved to be the best for image classification techniques, models based on CNN alone were considered in this study. We compared the performance of smallCNN with three pre-trained CNN models namely, AlexNet, ResNet-50, and VGG-16. SmallCNN is the CNN model built by us with fewer parameters and suitable for small datasets. The crop tested in this research is Oryza Sativa (Asian Rice) commonly referred to as paddy which is cultivated in abundance in India. The input dataset was fed into the model after performing appropriate pre-processing techniques followed by segmentation. The best accuracy of 66.67% was achieved in the case of ResNet-50 with Adam as the optimizer at a learning rate of 0.0001.***

Keywords: CNN, Adam, SGD, RMSProp, Image processing, Rice diseases, AlexNet, ResNet-50, VGG-16.

I. INTRODUCTION

Agriculture is an important source of income for India as a country as it plays a crucial role in the economy by contributing towards 16% of the total GDP and 10% of total exports[1]. However, in comparison to the growth of other sectors, the overall share of agriculture in the GDP of the country has declined. The reason can be attributed to poor crop yield due to the occurrence of diseases and increased pesticide usage. Hence, early detection of diseases proves to be vital for combatting this hurdle.

Oryza Sativa commonly known as paddy is one of the major agricultural crops in the world as it acts as a staple diet for over 2.7 billion people [2]. Especially, speaking of India, in particular, holds a paramount significance as the country ranks as the second-largest producer of rice after China.

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But every year, the farmers face major problems due to water shortage, pests, and diseases in the plants accounting for up to 37% decrease in crop production. It is nearly impossible to detect the early signs of damage due to them being very minute and hence beyond human visual capacity. A possible solution is to go for expert analysis, but it is inconvenient and expensive for a farmer to consult an expert due to their distant availability. So, automatic early detection and classification of symptoms is a vital requisite for immediate diagnosis. This will help to prevent huge losses. Hence, there is a necessity to outline a mechanism that spontaneously identifies and provides the appropriate diagnosis for disease symptoms. These symptoms predominantly occur in various parts of the plants such as the leaves and the stem. Therefore, the recognition of meaningful patterns on plants, leaves, and stems plays an important role in the process. Hence, configuring an AI system that recognizes these meaningful patterns to perform detection and classification on the disease affected crops that will circumvent human involvement, leading to an accurate and objective decision regarding disease infection and its further diagnosis. Convolutional Neural Networks (CNN) need a lot of data for its training. It is observed that they give better results with an increase in the size of the dataset. But in certain applications due to practical difficulties, the amount of data available is fairly less. In this research, the efficiency and performance of CNNs were tested over less voluminous data.There are a lot of diseases affecting the rice crop but, three major rice diseases were considered for this paper- bacterial leaf blight, brown spot, and leaf smut. For this purpose, we used a sample of images on rice disease from UCI Berkeley. The dataset contains 40 images of each of three diseases- bacterial leaf blight, brown spot, and leaf smut. So, in total it is only 120 images. The entire dataset is categorized into two parts, 80% is the training set while the rest 20% being the testing set.

II. LITERATURE REVIEW

In order to identify plant field pests, Thenmozhi, Reddy [3] suggested a deep learning-based CNN system that also examined hyperparameter effects. The quality of the model was also compared with the pre-trained models incorporating transfer learning. Yin, Shao, Zhang[4] proposed a hybrid model combining the benefits of CNN and Recurrent Neural Network(RNN) model for better classification accuracy. Lu, Yi, Zeng, Liu, Zhang[5] suggested the use of CNN for pattern recognition to yield good results. The models are trained to identify ten commonly occurring rice diseases.

Using the ten-fold cross-validation approach,the suggested CNN-based model achieved significantly

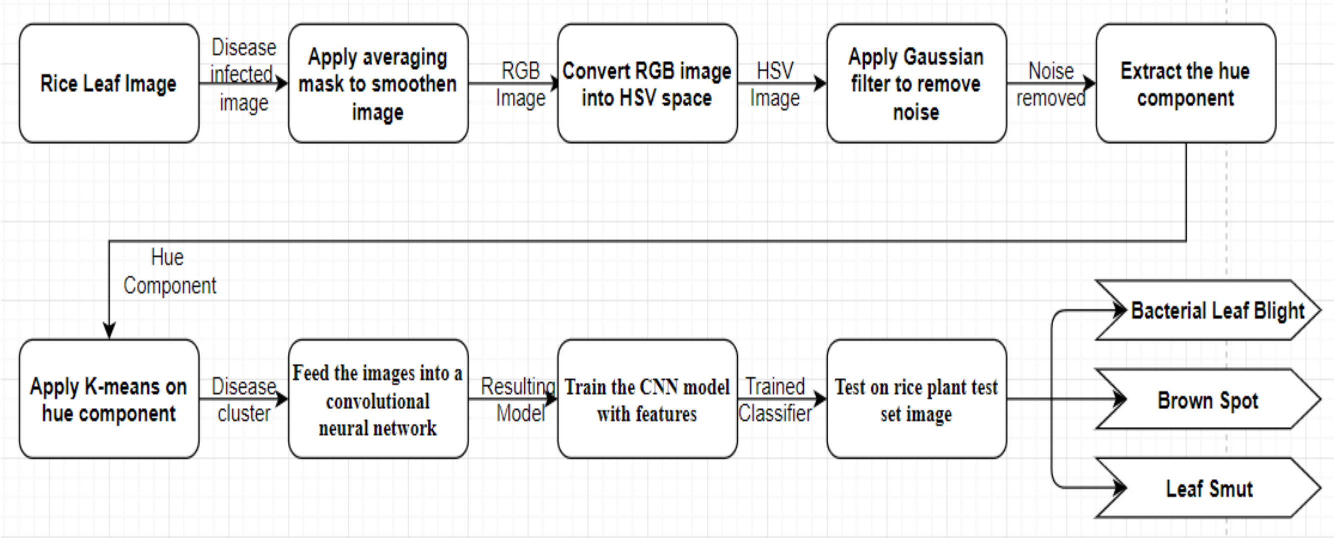

Fig. 1. Flowchart describing the Rice Classification Model

higher accuracy.Suma, Shetty, Tated, Rohan, Pujar[6] utilized an open image dataset and made use of various semi-supervised techniques and the convolution system to perform characterization of crop species and detect the magnitude of damage. Liang, Zhang, Cao[7] implemented a CNN-based rice blast recognition approach. The features extracted were far more distinct and effective than conventional approaches such as LBPH and Haar-WT. Ks, Sahayadhas[8] proposed an algorithm that concentrates on a particular problem to predict the disease using initial symptoms. They implemented automatic detection methods for image segmentation on rice leaves over a range of environmental conditions for further analysis. Iqbal, Khan, Sharif, Shah, Rehman, Javed[9] puts forth a survey on the different methods pertaining to the detection and the classification of citrus plant leaf diseases.

Rajmohan, Pajany, Rajesh, Raman, Prabu [10] have outlined a Sensor-based Mobile App framework. It finds out the affected disease based on disease infected crop images using deep CNN & SVM classifier. The proposed methodology is compared with the previous approaches which were implemented by combining k-means & fuzzy logic classifier and KNN & SVM classifier. Joshi, Jadhav[11] suggested classifying the extracted features using MDC and KNN. Kaur, Bhardwaj[12] developed an image processing system that can identify and classify the various ricediseases affecting rice cultivation. In disease detection, the disease affected portion of the rice plant is first identified using KNN and Clustering classifier. The identification of disease is done using KNN and SVM. Nidhis, Pardhu, Reddy, Deepa[13] exploited image processing techniques to identify the disease and determine the degree of the spread by estimating the percentage of the area of damage. Atole, Park[14] examined the effectiveness of the deep CNN in performing rice disease classification based on leaf images. A deep network called the AlexNet was implemented along with the usage of transfer

learning to increase the efficiency. Barbedo [15] put forth an article presenting a detailed analysis of various factors affecting deep neural networks when applied to plant

pathology. It also suggested possible solutions and future perspectives regarding the technology.

III. METHODOLOGY

These are the following steps that were taken as depicted in Fig. 1.

A. Pre-Processing

The first step involves applying an averaging mask to smoothen the image followed by changing the color space from RGB to HSV. The RGB model specifies a color as an additive of three primary components namely, Red, Green, and Blue whereas in HSV, hue and saturation values are taken into consideration. The process is then followed by the application of the Gaussian filter that facilitates noise reduction by smoothing the image and reducing contrast.

B. Segmentation

K-means clustering algorithm is utilized to perform segmentation over the pre-processed images. It aids in partitioning the area of interest (i.e.) the diseased part from the background. The K value was set to 3 to obtain three clusters- background, infected and green. Fig. 2,3, and 4 depict the sample results obtained after performing pre-processing and segmentation of one image of each of the three diseases.

C. Classification

The segmented image is classified into one of the three classes using the CNN approach. For this purpose, the performance of a small CNN model along with three pre-trained CNN models- AlexNet, ResNet-50, and VGG-16 is considered using three optimizers namely, SGD, RMSprop, and Adam over a range of different learning rates. Categorical cross-entropy was taken as the loss function.

1. Bacterial Leaf Blight

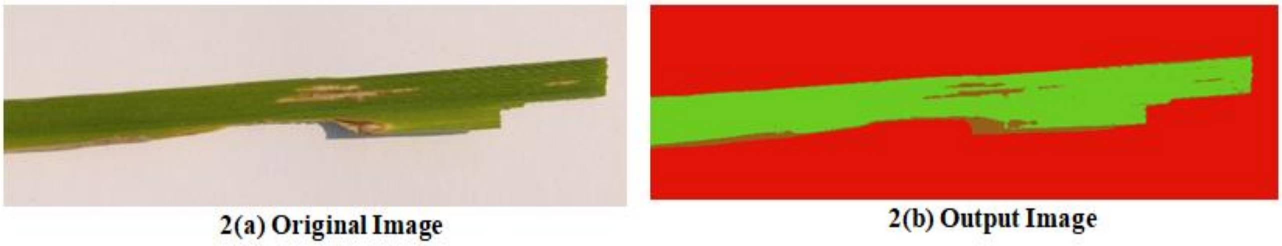

Fig. 2: (a) Original input image and (b) Preprocessed and segmentedimage

2. Brown Spot

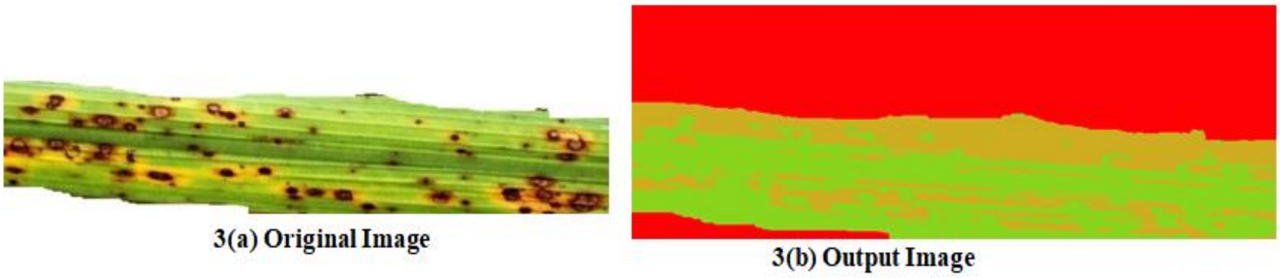

Fig. 3: (a) Original input image and (b) Preprocessed and segmented image

3. Leaf Smut

Fig. 4: (a) Original input image and (b) Preprocessed and segmented image

IV. CONVOLUTIONAL NEURAL NETWORK

A. Layers of CNN

It isa deep learning algorithm[16] that inputs an image, allocatesimportance (involving weights and biases) to different image labels, and distinguishes one from the other. The spatial dependencies and temporal dependencies in an image are successfully captured using necessary filters. This model fares better due to the reusability of the weights and the lowering of the multitude of parameters involved. The trained network can thus better understand the dynamics of the image. It consists of the following layers:

- Convolutional Layers:These consist of kernels acting as a characteristic feature, being passed through the image, or to the feature maps that were produced by the previous layers in a deepCNN. The kernel is made topass through the image to produce a feature map that predicts the class to which each feature belongs.

- Max Pooling Layers: It retains the most significant information by only considering the maximum value in a certain filter region hence considerably reducing the amount extracted.

- Fully connected layers: It is the last layer that converts the output of the previous layers into a single vector to be fed into the classification output of a CNN.

B. Batch Normalization

This process [17]facilitates each layer to learn on its own without the aid of other layers.This, in turn, stabilizes the learning process while reducing the number of training epochs required in the training process.

C. Categorical Cross-Entropy

It[18] is a combination of Softmax function alongwith Cross-Entropy loss used for multi-class classification. It compares the probability distribution with the true prediction distribution wherein the true class is a one-hot encoded vector. The closer the output values are to this particular vector, the lower the loss.

The formula is given in (1) where s_p signifies CNN score for positive class whereas s_j is the score for other classes.

$$CE = -\log\left(\frac{e^{s_p}}{\sum_j^C e^{s_j}}\right) \qquad (1)$$

D. Activation Function

i. Rectified Linear Unit Function (ReLU)

It[19]is one of the most frequentlyapplied activation functions in deep learning.The function returns 0 on receiving negative input, whereas, for positive values z, it returns the same value as shown in (2).

$$f(z) = \max(0,z) \qquad (2)$$

ii. Softmax

It[19] is a non-linear sigmoid function used to handle multiple classes. It takes a vector of real numbers as input performs probability distribution over it to classify the input into the appropriate label. The formula is given in (3) where z is passed as an argument.

$$\sigma(z)_j = \frac{e^{z_j}}{\sum_{i=1}^{K} e^{z_i}} \; for\ j = 1\ to\ K \qquad (3)$$

E. Optimizers

i. Stochastic Gradient Descent(SGD)

This optimizer[20] works on an iterative basis wherein itenhances the smoothness properties of a function. It replaces the exact gradient calculated from the dataset with an estimate also known as the stochastic approximation.The equation is given in (4) wherein θ means parameter, η is the learning rate,∇ signifies the gradient, and J is the loss function.

$$\theta = \theta - \eta \cdot \nabla_\theta J(\theta; x, y) \qquad (4)$$

ii. Root Mean Square Propagation(RMSprop)

This optimizer[21] is quite comparable to the SGD with momentum in terms of how the gradients are calculated. It is done by considering each weight's squared average and then dividing it by the square root of the mean square.The equation is given in (5) wherein θ means parameter, η is the learning rate, γsignifies decay term and

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{(1-\gamma)g_{t-1}^2 + \gamma g_{t+\varepsilon}}} \cdot g_t \qquad (5)$$

iii. Adaptive Moment Estimation(Adam)

It[22]is a combination of RMSprop and Stochastic Gradient Descent along with momentum. It exploits the squared gradients to calibrate the learning rate and uses momentum by using shifting the average of the gradient like SGD with momentum.The equation is given in (6) wherein θ means parameter, η is the learning rate,∇ signifies the gradient, andJ is the loss function.

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{\widehat{v_t}} + \epsilon}\widehat{m_t} \qquad (6)$$

V. VARIOUS CONVOLUTIONAL NEURAL NETWORKARCHITECTURES

A. AlexNet

The network[23]consisted of 5 convolutional, 3 fully connected layers and 3 max pooling. A Rectified Linear Unit (ReLU) is applied after every convolutional layer to enhance the non-linearity. Further, batch normalization is applied after

every layer to increase classification accuracy. The fully connected layers are provided with a dropout ratio of 0.4 to avoid overfitting. The first two fully connected layers hold 4096 neurons each whereas the final layer has 1000 neurons. These layers are connected to the softmax activation layer consisting of three neurons defined by the number of insect classes. Fig. 5 depicts the AlexNet architecture.

B. ResNet-50

The network[24] contains a convolutional layer, a max-pooling layer, 16 residual blocks, an average pooling layer and a fully connected layer followed by the Softmax activation layer consisting of 3 classes. The main function of residual blocks is to improve the depth of the network by decreasing the size of the output. Fig. 6 shows the ResNet – 50 architectural blocks.

C. VGG-16

This model[25]comprises of consecutively aligned convolution layers separated by max-pooling layers. These layers are then connected to two fully connected layers followed by softmax output with 3 neurons. ReLU activation is applied to each convolution layer as well as the fully connected layer. The dropout ratio is adjusted to the value of 0.5 to control overfitting. Fig. 7 depicts the VGG-16 architecture.

D. SmallCNN

We implemented a smallCNN model having six convolutional layers, three fully connected layers and five max-pooling layers followed by a softmax classifier (C set to 3). We termed it as small CNN since a lesser number of filters or kernels are used in each convolutional layer compared to other pre-trained CNN. Since a lesser number of filters were used, the number of tunable parameters got decreased a lot which in turn reduces the training time to a great extent. Further, the ReLU layer and Batch Normalization were applied after each convolutional layer to increase the efficiency of the model. The three fully connected layers consisted of 1200, 600 and 150 neurons respectively with the dropout ratio set to 0.5, 0.4 and 0.4 respectively. Fig. 8 depicts the smallCNN architecture.

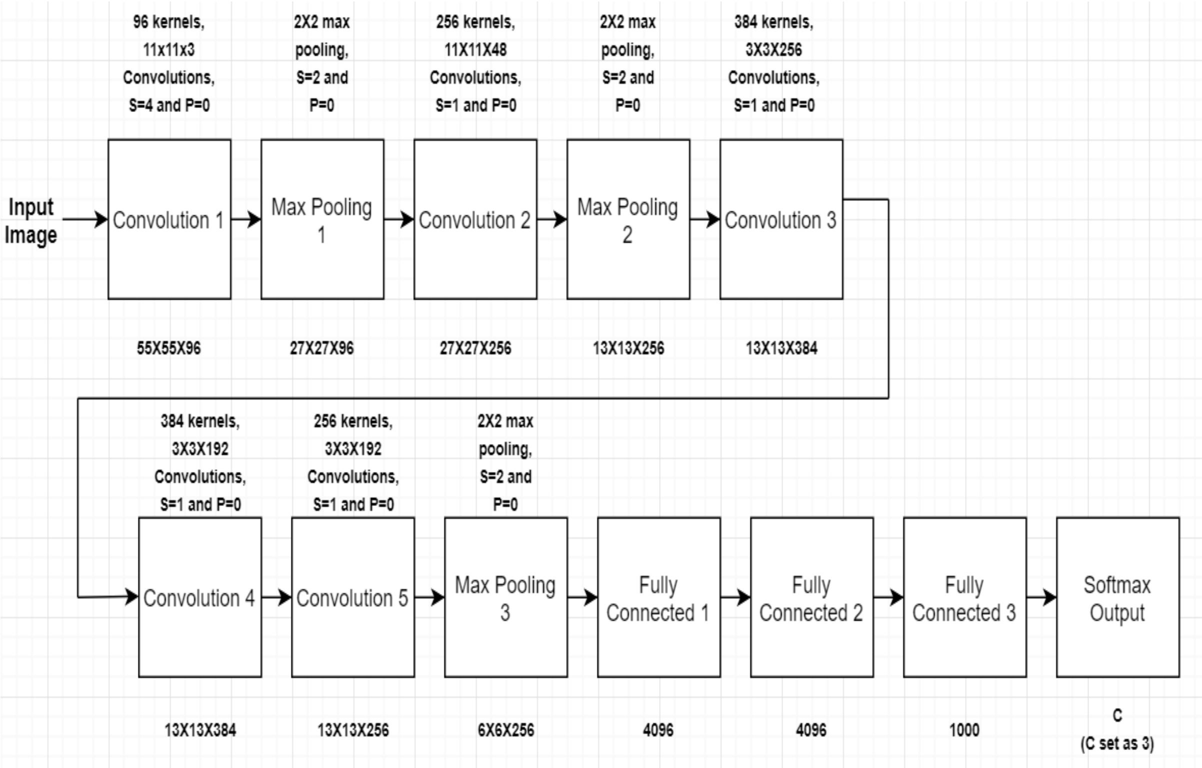

Fig. 5. AlexNet Model

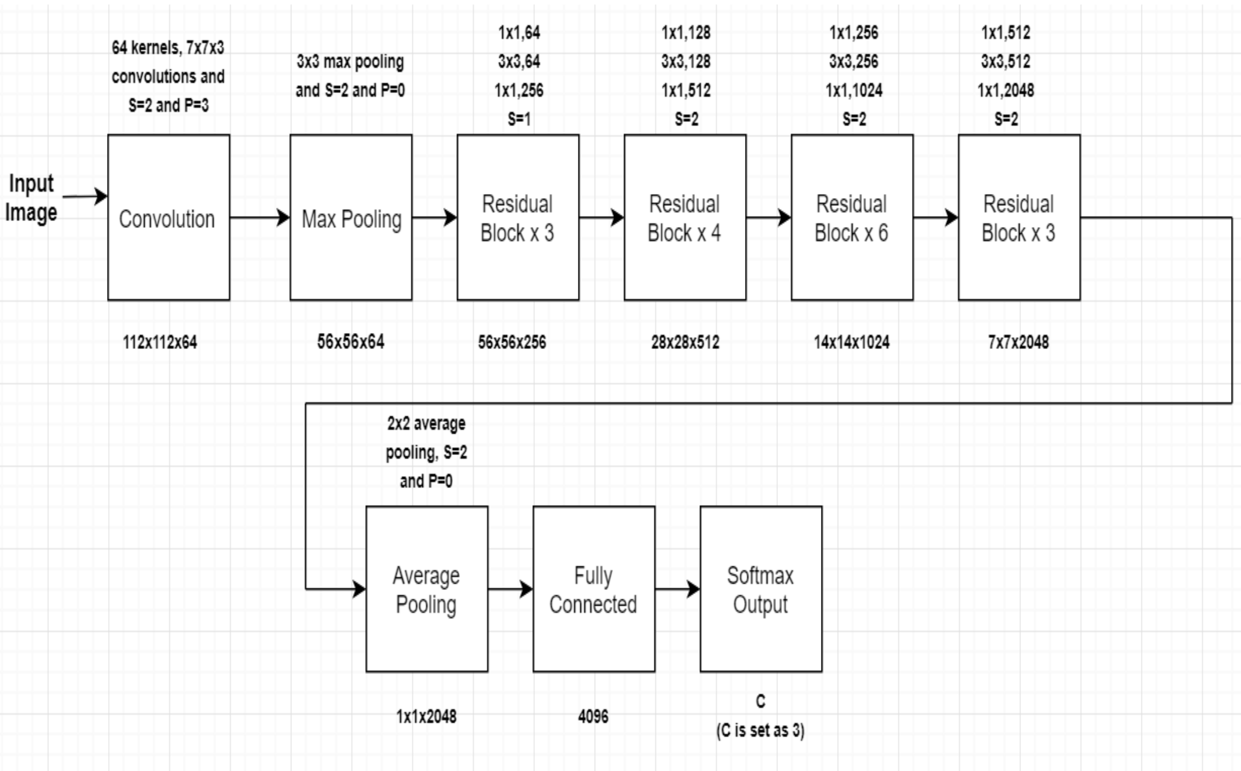

Fig. 6. ResNet-50 Model

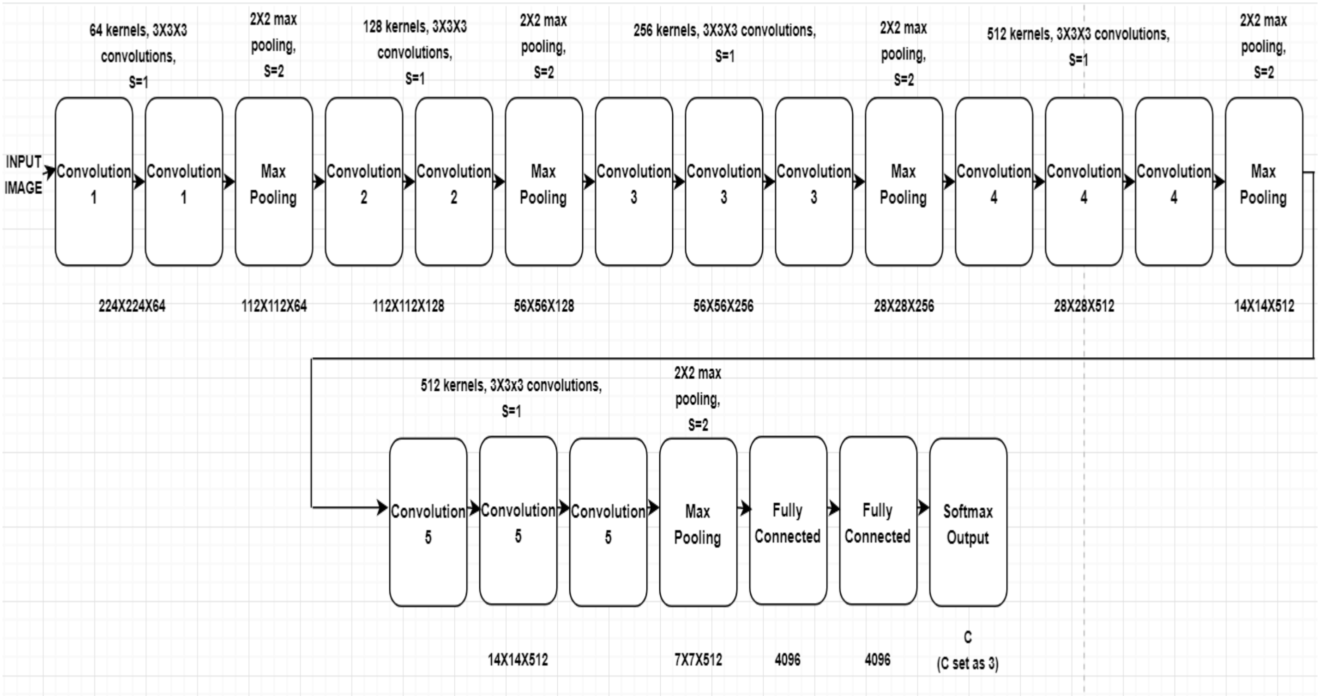

Fig. 7. VGG-16 Model

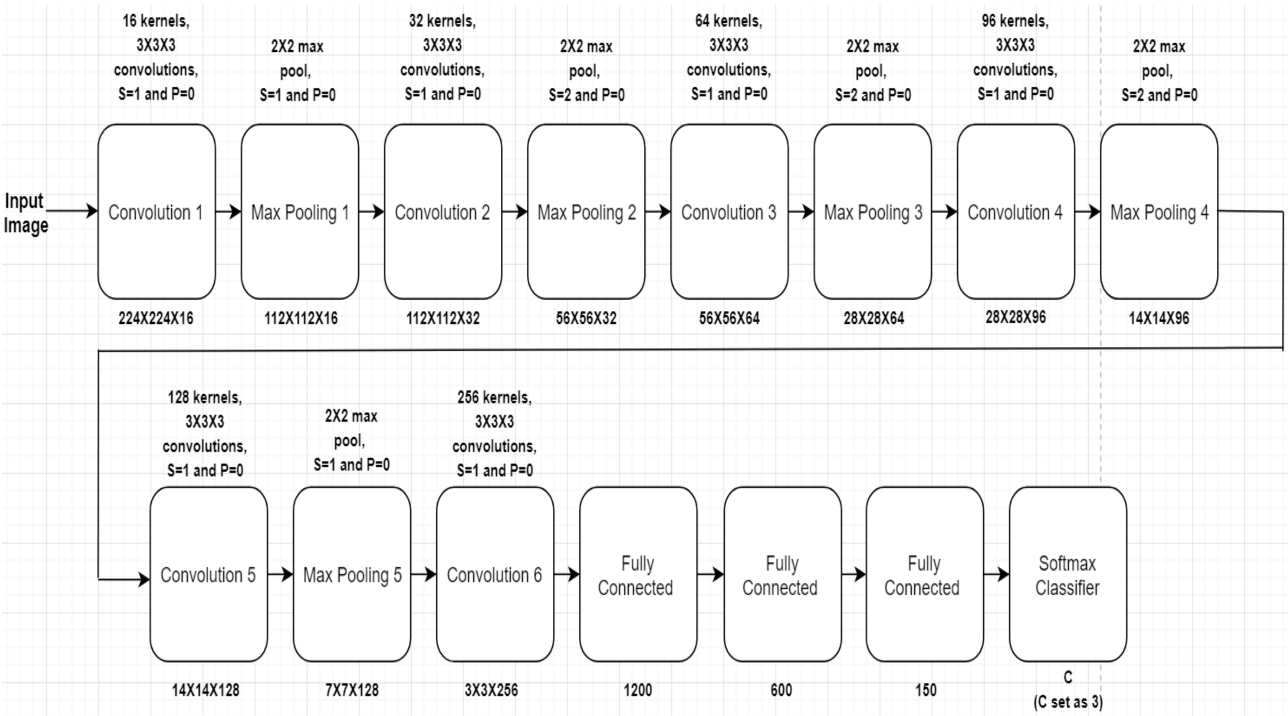

Fig. 8. SmallCNN Model

VI. RESULTS AND DISCUSSION

A. Validation Accuracy

We trained the dataset on four models using different optimizers over a range of four learning rates- 0.01, 0.001, 0.0001 and 0.0005 over 10 epochs from which the maximum value was selected. Table-I depicts the accuracy of the CNN models on different learning rates. Additionally, a graphical representation has been done in Fig 9, 10 and 11 representing the performance of each model on different optimizers. The maximum accuracy of 66.67% was achieved in the case of ResNet-50 with Adam as the optimizer at a learning rate of 0.0001. The lower learning rate ensured the smooth and steady increase in accuracy for every epoch. Also, the gradient vanishing problem was well handled in ResNet-50 than other CNN models. However, the major reason behind low accuracy rates in all the models can be attributed to the use of a relatively small dataset. It is expected that all the above CNN models will give better performance when it is trained with a larger dataset. In the case of SGD, maximum accuracy was achieved using ResNet-50 at a learning rate of 0.0001.

Performance-wise, the pre-trained models fared better than the smallCNN model. In RMSprop, we get the maximum accuracy at 0.001 using smallCNN at a value of 62.5%. The smallCNN model produced better results than the others comparatively.

However, in Adam, 66.67% was the maximum accuracy achieved with ResNet-50 at a learning rate of 0.0001. Also, it was observed that AlexNet and VGG-16 were not at its best with the smaller datasets as its performance was poor.

B. Validation Loss

Categorical Cross-Entropy loss was used as a loss function. The values observed at the 10th epoch are depicted in Table-II. AlexNet and VGG-16 showed high values for all optimizers except SGD with AlexNet being on the higher side. ResNet-50 showed low values for Adam as compared to SGD and RMSProp. It is also very interesting to note that VGG-16 exhibited constant value at all learning rates for a specific optimizer wherein the value for SGD was low as compared to the other two. SmallCNN had significantly lower values for all the optimizers at all learning rates. The primary reason for lower losses in smallCNN is due to its lesser number of tunable parameters and the mitigation of the gradient vanishing problem when compared with other CNNs. Hence, in this scenario, SmallCNN fared the best followed by ResNet-50, VGG-16, and AlexNet.

Table-I: Validation accuracy values of different CNN models over different learning rates using different optimizers

CNN Models	OPTIMIZERS											
	ADAM				SGD				RMSProp			
Learning Rate	0.01	0.001	0.0001	0.0005	0.01	0.001	0.0001	0.0005	0.01	0.001	0.0001	0.0005
AlexNet	0.3750	0.3333	0.4167	0.3333	0.4167	0.3750	0.4167	0.5000	0.3333	0.3333	0.3333	0.4167
ResNet-50	0.4167	0.4167	0.6667	0.5000	0.4167	0.5833	0.4167	0.4167	0.5417	0.5833	0.4167	0.4167
VGG-16	0.3333	0.3333	0.3333	0.3333	0.5000	0.4167	0.4167	0.4167	0.3333	0.3333	0.3333	0.3333
Small CNN	0.3333	0.3750	0.3333	0.3333	0.3333	0.5000	0.4167	0.3750	0.4167	0.6250	0.4583	0.3333

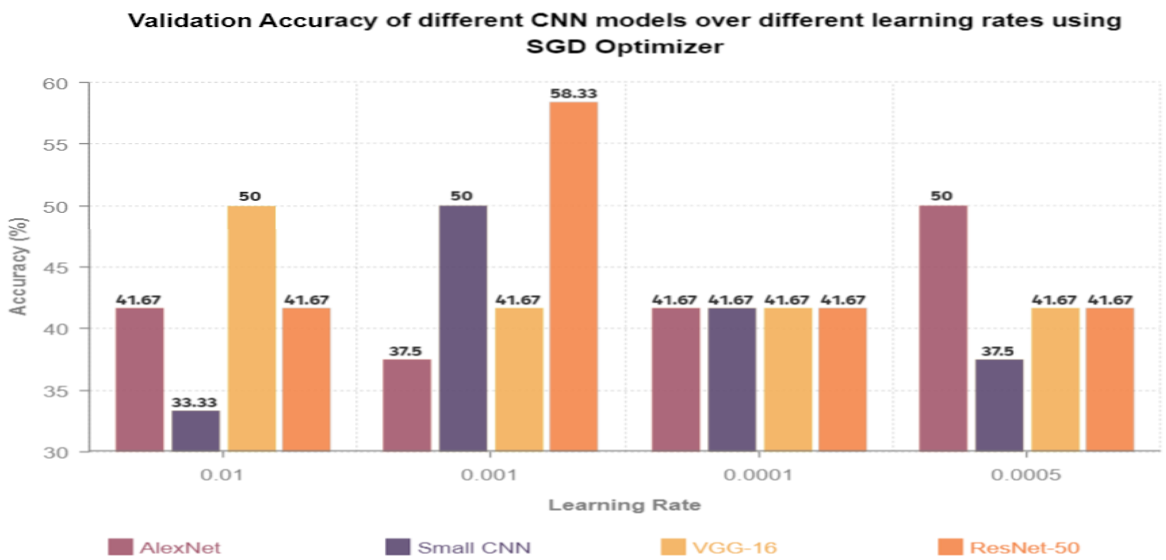

Fig. 9. Validation Accuracy of different CNN models over different learning rates using SGD optimizer

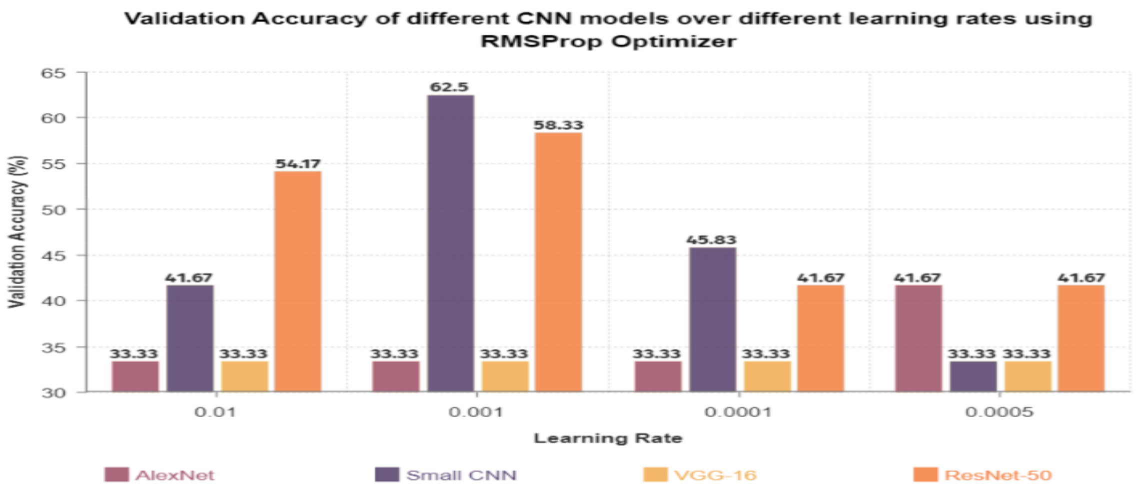

Fig. 10. Validation Accuracy of different CNN models over different learning rates using RMSprop optimizer

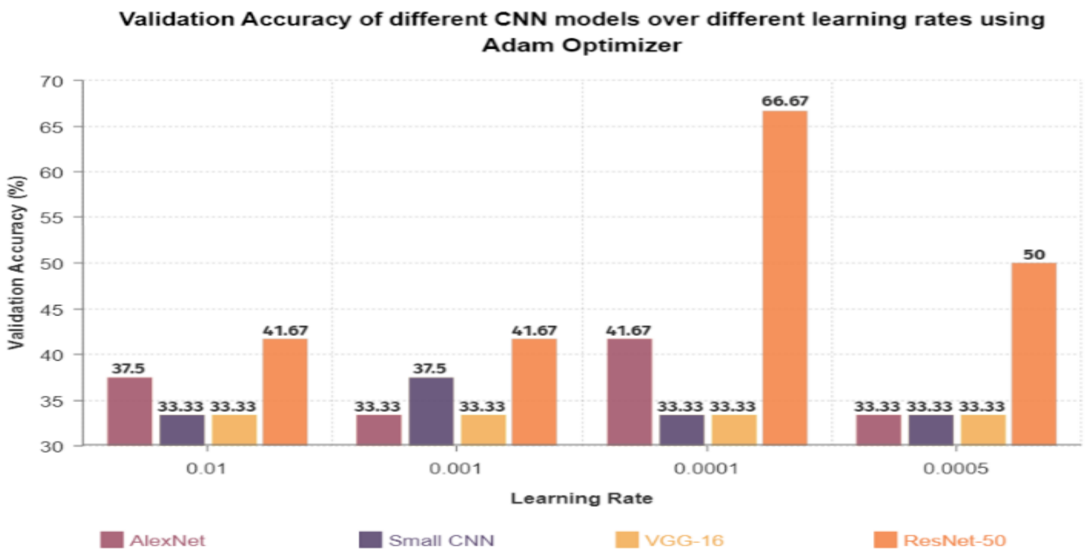

Fig. 11. Validation Accuracy of different CNN models over different learning rates using Adam optimizer

Table-II: Validation loss values of different CNN models over different learning rates using different optimizers

CNN Models	OPTIMIZER											
	ADAM				SGD				RMSProp			
	0.01	0.001	0.0001	0.0005	0.01	0.001	0.0001	0.0005	0.01	0.001	0.0001	0.0005
AlexNet	24.65	52.99	7.89	30.95	1.09	1.12	1.07	1.11	12.23	24.25	24.85	12.07
ResNet-50	2.66	8.34	3.29	2.34	12.08	13.43	7.84	9.40	2.53	8.06	12.09	6.92
VGG-16	10.75	10.75	10.75	10.75	1.09	1.09	1.09	1.09	10.75	10.75	10.75	10.75
Small CNN	2.15	1.70	1.70	1.56	1.14	1.12	1.10	1.10	1.54	1.57	1.59	1.60

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VII. CONCLUSION

In this study, we compared the accuracy of three pre-trained CNN models- AlexNet, ResNet-50, and VGG-16 along with a small CNN model and also studied the effect of

different learning rates while using various optimizers on the model. Inspite of a small dataset, we were able to achieve a maximum classification accuracy of 66.67% on the validation set using Resnet-50 with Adam as the optimizer ata learning rate of 0.0001. The validation loss was minimum in the case of smallCNN with SGD optimizer at the learning rates of 0.0001 and 0.0005 wherein a loss value of 1.10 was encountered. Therefore, while the smallCNN model suffered from low accuracy, it had the lowest loss values as compared to the pre-trained ones.The accuracy is low in terms of normal standardsdue to the experiments being conducted with very small datasets. It is expected that accuracy will improve with a substantial increase in data volume and by using much better pre-processing techniques. Hence, our future work will revolve around using better image pre-

processingtechniques along with gathering more relevant data for the training purpose. Efforts will also be taken in the direction of improving the small CNN model to perform better than the pre-trained ones.

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