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A Novel Convolutional Neural Networks Based Spinach Classification and Recognition System

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Abstract: In the present scenario, Deep Learning (DL) is one of the most popular research algorithms to increase the accuracy of data analysis. Due to intra-class differences and inter-class variation, image classification is one of the most difficult jobs in image processing. Plant or spinach recognition or classification is one of the deep learning applications through its leaf. Spinach is more critical for human skin, bone, and hair, etc. It provides vitamins, iron, minerals, and protein. It is beneficial for diet and is readily available in people's surroundings. Many researchers have proposed various machine learning and deep learning algorithms to classify plant images more accurately in recent years. This paper presents a novel Convolutional Neural Network (CNN) to recognize spinach more accurately. The proposed CNN architecture classifies the spinach category, namely Amaranth leaves, Black nightshade, Curry leaves, and Drumstick leaves. The dataset contains 400 images with four classes, and each type has 100 images. The images were captured from the agricultural land located at Thirumanur, Salem district, Tamil Nadu. The proposed CNN achieves 97.5% classification accuracy. In addition, the performance of the proposed CNN is compared with Support Vector Machine (SVM), Random Forest, Visual Geometry Group 16 (VGG16), Visual Geometry Group 19 (VGG19) and Residual Network 50 (ResNet50). The proposed provides superior performance than other models, namely SVM, Random Forest, VGG16, VGG19 and ResNet50.

Keywords: Accuracy; convolutional; deep learning; plant; neural networks; spinach

1 Introduction

In India, agriculture is one of the significant activities to sustain livelihoods and increase food production. Agriculture is one of predominant role in the growth of economy in the country. India is the second largest producer of wheat and rice, the world's major food staples. India is currently the world's second largest producer of several dry fruits, agriculture-based textile raw materials, roots and tuber crops, pulses, farmed fish, eggs, coconut, sugarcane and numerous vegetables. In India, the population will be estimated to reach 1.5 billion. There is a demand of natural resources due to the population growth in the world. The India has only 2.2% geospatial area in the world that taking care of 18% and 15% of humans and livestock respectively [1–7].

Spinach is a kind of vegetable with lots of nutrients and fewer calories. Spinach is more critical for human skin, bone, and hair, etc. It provides vitamins, iron, minerals, and protein. It is beneficial for diet and is readily available in people's surroundings [8–15]. Most of the spinaches look-wise appear in the same manner. Therefore, urban people and children cannot differentiate and recognize spinach's name. Several researchers have proposed machine learning and DL algorithms to overcome these limitations. In recent years, the DL algorithms have provided promising results in terms of accuracy [16–18]. Hence, the current researchers have used various pre-trained models and the proposed CNN model to provide the accuracy of spinach classification [19–24].

DL is a sub field of Machine Learning (ML). However, ML is a subset of AI. In DL, the neural networks replicate or imitate the behavior of human brain. Generally, the ML performs the process of feature extraction and transformation. Each layer gets the input from the output of previous layer. DL models are able to extract the proper features by themselves. It is mostly suitable for large amount of input and output data. In DL, Deep Neural Network (DNN) follows NN with multiple hidden layers between output and input layers. The primary objective of NN is to get the set of inputs and perform the complex operation and finally will provide the classification output. The DL applications are self-driving cars, news aggregation and fraud news detection, natural language processing, virtual assistants, entertainment, visual recognition, fraud detection, healthcare, etc. One of the most used networks in DNN is CNN, which is mostly used for image categorization [25–27].

CNN is a kind of Neural Networks (NN) that allows the input images to extract the low-level features in an understandable human way for better classification. The CNN model's primary advantage is detecting essential elements to classify an image without human support. For example, let's assume dogs and cats are present in the dataset that learns different features for each class category by the model itself. Existing researchers presented various pre-trained and novel CNN models still need to improve spinach classification accuracy [28–31].

This paper presents a novel CNN to recognize spinach more accurately. The proposed CNN architecture classifies the spinach category into four subcategories: amaranth leaves, black nightshade, curry leaves, and drumstick leaves. The dataset contains 400 images with four classes, and each class has 100 images. The images were captured from the agricultural land located at Thirumanur, Salem district, Tamil Nadu.

The highlights of the author's contribution are follows:

- Various analyzes have been conducted with various deep learning models in the literature review and identified their limitations.
- The authors propose the novel CNN to classify the spinach category, namely amaranth leaves, black nightshade, curry leaves, and drumstick leaves.

- To increase the accuracy of spinach classification, the authors varied the training and validation ratio from the dataset and finalized the best ratio for spinach classification.

The paper's organization is as follows: Section 2 discusses the related work. Section 3 proposes a novel CNN model to classify the spinach categories by their leaves. Section 4 summarizes the research result and discussions. Section 5 presents a discussion of the results and recommendations for future work.

2 Related Works

This section discusses the various deep learning algorithms to recognize and classify the spinach.

Islam et al. [32] proposed a DL-based local spinach classification system. It is identified in the spinach category automatically from Bangladesh spinach leaves. The dataset contains five types and, altogether, around 3885 images. To increase the accuracy of spinach classification, this paper performed a performance comparison among existing pre-trained models. Before being applied to the proposed model, the input dataset images have undergone preprocessing operations such as image color conversion, filtering, rescaling, and resizing. Later, the preprocessed images were applied to various pre-trained models to perform the classification. In this section, we examine and contrast the performance of the various pre-trained models. It can be seen that the VGG16 has the best accuracy of 97 percent when compared to other models that have already been trained.

Koyama et al. [33] proposed an ensemble model to predict the freshness of spinach from its leaves. This work considered the dataset that contains four classes of 1045 images. Here, the authors have adopted complicated labeling with probabilistic techniques and soft labeling with ensemble techniques to identify the freshness of the spinach. The performance was evaluated, and the ResNet model provided the maximum accuracy among other pre-trained models. The proposed model provides an accurate prediction of freshness evaluation with respect to human. However, human judgment varies, and freshness may not be absolute.

Zhu et al. [34] presented various machine learning algorithms to identify the freshness of spinach leaves. The spinach leaves are captured at different temperatures and time durations. The dataset images are captured by hyperspectral imaging technology. The authors used Principal Component Analysis (PCA) to perform the qualitative analysis. The authors compared the performance with SVM, Partial Least Square-Discriminant Analysis (PLS-DA), and Extreme Learning Machine (ELM). The ELM method is provided a better result than SVM and PLS-DA.

Kanda et al. [35] proposed a DL-based plant disease classification. This paper uses three techniques. First, the conditional generative adversarial network is used to create the synthetic data. Second, CNN is utilized to extract the features from the input data. Finally, the extracted features are applied to logistic recursion to perform the classification. This work is considered eight datasets. The efficacy of the proposed method is analyzed, and the average accuracy is 96% for all eight datasets. The proposed method's efficacy is evaluated in comparison to that of other current approaches.

Ramkumar et al. [36] proposed the ResNet-50 model based on spinach's cercospora identification. cercospora is a disease that occurs in spinach leaves. To classify the cercospora affected leaves and not affected leaves, this paper proposed the ResNet-50 pre-trained model. The preprocessing operation is performed on the dataset. Later, the segmentation process is carried out using the preprocessed images as input. Finally, the ResNet-50 model has classified the spinach leaves. The proposed ResNet-50 has provided more training and testing accuracy.

Koyama et al. [37] proposed ML based spinach classification. The spinach leaves images are captured from smart phone. Then, the authors are removed the background of the spinach images. The background removed images are converted to gray scale and Lab and Hue Saturation Value (HSV). The mean, median, variance are extracted from spinach leaves. The local features are extracted using Features from Accelerated Segment Test (FAST) and Binary Robust Independent Elementary Features (BRIEF) feature detectors. The selected features are applied to machine learning algorithm, namely SVM to classify the spinach leaves. The proposed model is obtained 84% accuracy for two class dataset.

Christopher [38] proposed a disease recognition system based on spinach images. The histogram technique is used to fine-tune the intensity and contrast of the image. The segmentation technique is used to segregate the disease-affected portion. A morphological operation is used to remove the protrusion portion from the images. The Histogram of Oriented Gradients (HOG) feature extraction method is used to extract the features. Finally, Artificial Neural Networks (ANN) is used to classify the disease-affected and non-affected leaves. Moreover, it has required less computation time and provided more accuracy.

Bisen [39] proposed a Deep CNN-based plant classification using the leaf. This paper proposed an automated plant name identification system to overcome this drawback. It is accomplished using CNN with more accuracy. This work consists of image preprocessing, feature extraction, and image recognition. The image preprocessing is performed using the image augmentation technique. The CNN is used to perform the feature extraction and classification. This work is considered the Swedish leaf dataset with 15 classes. Finally, it has provided 97% accuracy.

Raj et al. [40] proposed a dual DL architecture for plant classification. This work is considered within its own dataset (Leaf 12). The Efficient convolutional Neural Network for Mobile Vision Application (MobileNet) and Densely Connected Convolutional Networks-121 (DenseNet-121) have agreed to use the proposed work.. The result of the proposed MobileNet and DenseNet-121 with LR classifier has provided the maximum accuracy when compared to other pre-trained models. Furthermore, the proposed Dual DL architecture is more computationally efficient than other pre-trained and other neural networks.

Liu et al. [41] proposed a hybrid DL model for plant classification. This paper proposed a hybrid classification algorithm that combines the Auto Encoder and CNN. It is proved that the proposed hybrid DL algorithm extracts the features more accurately. Later, the plant images are classified using the SVM algorithm. The proposed hybrid DL with SVM algorithm performs superior to SVM, Autoencoder, and CNN. The performance of the proposed hybrid DL with SVM algorithm, SVM, and CNN + SVM is 93%, 88%, and 91%, respectively.

Wagle et al. [42] proposed the classification of plant species using compact CNN and Alex Krizhevsky Convolutional Neural Networks (AlexNet) with transfer learning. The dataset contains nine classes. The proposed DL model is trained using leaf images with different augmentation techniques. In addition, the proposed models, i.e., structure-wise changes in CNN, namely N1, N2, and N3, are trained and tested with the Flavia dataset with 32 classes. The accuracy of the N1 model is 99.45%, whereas the recommended model N2 is 99.65%. The accuracy of the Model N3 is 99.55%, whereas the accuracy of the AlexNet model is 99.77%. The proposed model is provided better accuracy than all other models.

Sakai et al. [43] proposed vegetable recognition using CNN. This paper proposed a deep neural network to recognize the object thru the extracted features. The implementation has been done using Python. We notice that the proposed CNN has provided superior performance than other models from the observation. The recognition rate of the proposed CNN has achieved 97.5%. Tab. 1 depicts the review of various spinach and vegetables classification using DL Models.

Table 1: Review of various spinach and vegetables classification

Author	Year	Vegetable type	Dataset type	Dataset size	Deep learning model	Accuracy (%)
Islam et al. [32]	2022	Spinach	Own	3885 images	VGG16	97%
Koyama et al. [33]	2022	Spinach	Own	1045 images	ResNet	85%
Zhu et al. [34]	2019	Spinach	Own	Not specified	ELM	92.5%
Kanda et al. [35]	2021	Plant	Own	1360 images	GAN + CNN + LR	98.5%
Ramkumar et al. [36]	2020	Spinach	Own	Not specified	ResNet-50	98.94%
Koyama et al. [37]	2021	Spinach	Own	Not specified	SVM	84%
Christopher [38]	2020	Spinach	Own	Not specified	ANN	98.7%
Bisen [39]	2020	Plant	UCI plant leaf	1125 images	CNN	97%
Raj et al. [40]	2019	Plant	Own dataset	Not specified	MobileNet + DenseNet-121 + LR	98.7%
Liu et al. [41]	2015	Plant	Own dataset	Not specified	Hybrid CNN + SVM	93%
Wagle et al. [42]	2021	Plant	PV dataset	32 classes	AlexNet	99.9%
Sakai et al. [43]	2016	Plant	Own	Not specified	CNN	97.55%

We observed that the researchers have used ML and DL techniques to classify the images from the related work [44–47]. Incredibly, most researchers have proposed their own CNN models and Pre-trained CNN models to improve the plant name or spinach name recognition classification accuracy [48–50]. It is noted that most of the pre-trained models do not provide high accuracy [51,52]. To improve the spinach classification accuracy, this paper proposes the novel CNN model. It uses its own dataset for spinach classification.

3 Materials and Methods

Fig. 1 depicts the whole process of the classification method. The dataset images are captured from agricultural land. It has been split into training and validation data. The proposed method performs the image preprocessing and classification operations. Finally, the trained model gets the new input images for classification. Here, we propose the novel CNN model for extracting the features and classification.

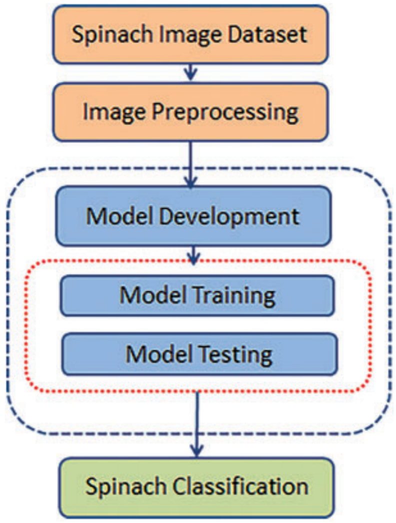

Figure 1: Overall work flow of classification method

3.1 Spinach Dataset

The spinach leaf dataset contains 400 images with four classes. The spinach class names are Amaranth Leaves, Black Nightshade, Curry Leaves, and Drumstick Leaves. Each class has a total of 100 images. The dataset images are taken from agricultural land in Thirumanur (latitude 11.5759° N, longitude 78.3320° E). It is located in Valapady taluk, Salem district in Tamil Nadu. The rows and columns of these images are 4160 and 3120 pixels, respectively. These dataset images were captured using a Redme smartphone with a 12-megapixel camera. Each photo was taken in the identical postures, and the portrait image was taken. Fig. 2 depicts a typical image from the spinach dataset.

Figure 2: Typical image from the spinach dataset

3.2 Image Preprocessing

Data preprocessing is one of the basic processes for implementing the model. In image preprocessing, various techniques are applied to raw images to increase the quality of the image. Here, the background is removed from all the images in the dataset images. Later, the image is resized to 256×256 pixels. Finally, the proposed CNN model gets the input size of 256×256. Fig. 3 depicts the sample preprocessed images.

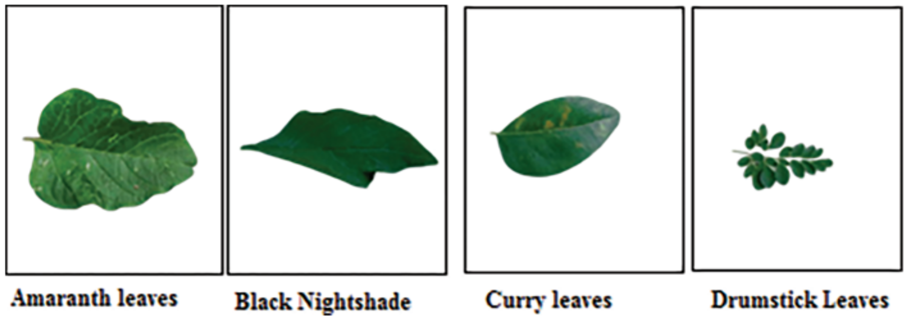

Figure 3: Sample preprocessed images

3.3 The Proposed Convolutional Neural Network Architecture

A CNN is a type of neural network that uses convolutional layers to classify images. The key terms are explained below.

- **Filter:** It detects the edges in an image by changing the intensity value.
- **Kernel:** It is a two dimensional matrix representation which holds the filters value.
- **Convolution:** It is a process that kernel values moves over the sub region input image and it performs the dot product in it.
- **Stride:** It is the number of pixels shift over the input matrix.
- **Padding:** It is a process of adding zeros to the input matrix.
- **Activation Function:** It determines whether or not a neuron should be activated.
- **Pooling:** It is a process to reduce the size of the image.

The proposed CNN model is illustrated in Fig. 4 for spinach classification.

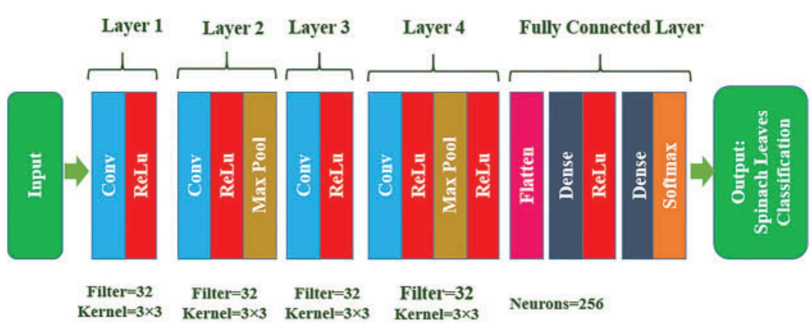

Figure 4: Proposed CNN architecture

In the first convolution layer, the proposed CNN model performs the convolution operation with a kernel size of 3×3, and the number of filters is 32. It uses a stride size of 1. After completing the convolution operation, the CNN model applies the ReLu activation function to activate the number of neurons present in the first layer. Moreover, it uses the padding type to be the same, i.e., the output of the first layer will also be maintained at the same size.

Convolution is a process that kernel values moves over the sub region input image and it performs the dot product in it. The convolution process is represented in Eq. (1).

$$FM = I \times F \tag{1}$$

where FM, I and F indicate feature map, input image and kernel size, respectively.

In CNN, the padding is either valid or same. If we consider that the padding size is same, it is computed in Eq. (2).

$$Padding_{width} = \frac{K-1}{2} \tag{2}$$

where K indicates the kernel size.

In each layer, output matrix or image depends on the stride, padding and it is calculated using Eq. (3).

$$I_{out} = \frac{I_{in} + (2 \times Padding_{width}) - K}{S} \tag{3}$$

where I_{in}, I_{out}, K and S indicate input image, output image, kernel and stride, respectively.

Pooling is commonly used to decrease the dimensionality of an image. Max pooling is the process that extract the maximum value of convolution operation and it is calculated in Eq. (4).

$$Max\_Pool = (FM_h - K + 1/\ \ S \times (FM_w - K + 1)\ /\ \ S \times FM_c) \tag{4}$$

where FM_h, FM_w, FM_c, K and S indicate height of feature map, width of feature map, number of channels in FM, kernel size and stride.

Normalizing the output in each layer is possible using the activation function. For the activation function, we used the Rectified Linear Unit (ReLU). In ReLU, the value will be zero if the input value is less than 0. Otherwise, the output of the respective layer is the raw value of the input. The ReLU activation function is calculated using Eq. (5).

$$ReLU\,(I) = \begin{cases} 0 & if\ I < 0 \\ I & if\ I \geq 0 \end{cases} \tag{5}$$

where I is input image of each layer

The second convolution layer performs the convolution operation with a kernel size of 3 × 3, the number of filters is 32, and the stride size of 1. After completing the convolution operation, the CNN model performs the ReLu activation function. Later, it performs the max pooling with a size of 8 × 8.

The third convolution layer performs the convolution operation with a kernel size of 3 × 3. The number of filters is 32, and the stride size of 1. After completing the convolution operation, the CNN model performs the ReLu activation function.

The fourth convolution layer performs the convolution operation with a kernel size of 3 × 3. The number of filters is 32, and the stride size is 1. After completing the convolution operation, the CNN model performs the ReLu activation function. Then, it performs the max pooling with a size of 8 × 8. Later, it performs the ReLu activation function.

The fifth convolution layer is a fully connected layer. This layer starts with a flattening operation and neurons size of 256. The model then generates the dense layer with the ReLu activation function. Again, the model generates a dense layer with four neurons using the softmax activation function. It is one of the activation functions which can be used in the last layer. It is suitable for multi class classification and its calculation is given in Eq. (6).

$$\sigma\,(I)_l = \frac{exp^{I_l}}{\sum_{j=1}^{k} exp^{I_j}} \tag{6}$$

where σ, I, k, exp^{I_l}, exp^{I_j} indicate softmax, input image, exponential function for input and The feature v exponential function for output, respectively. The feature map of sample amaranth leave visualization is shown in Fig. 5.

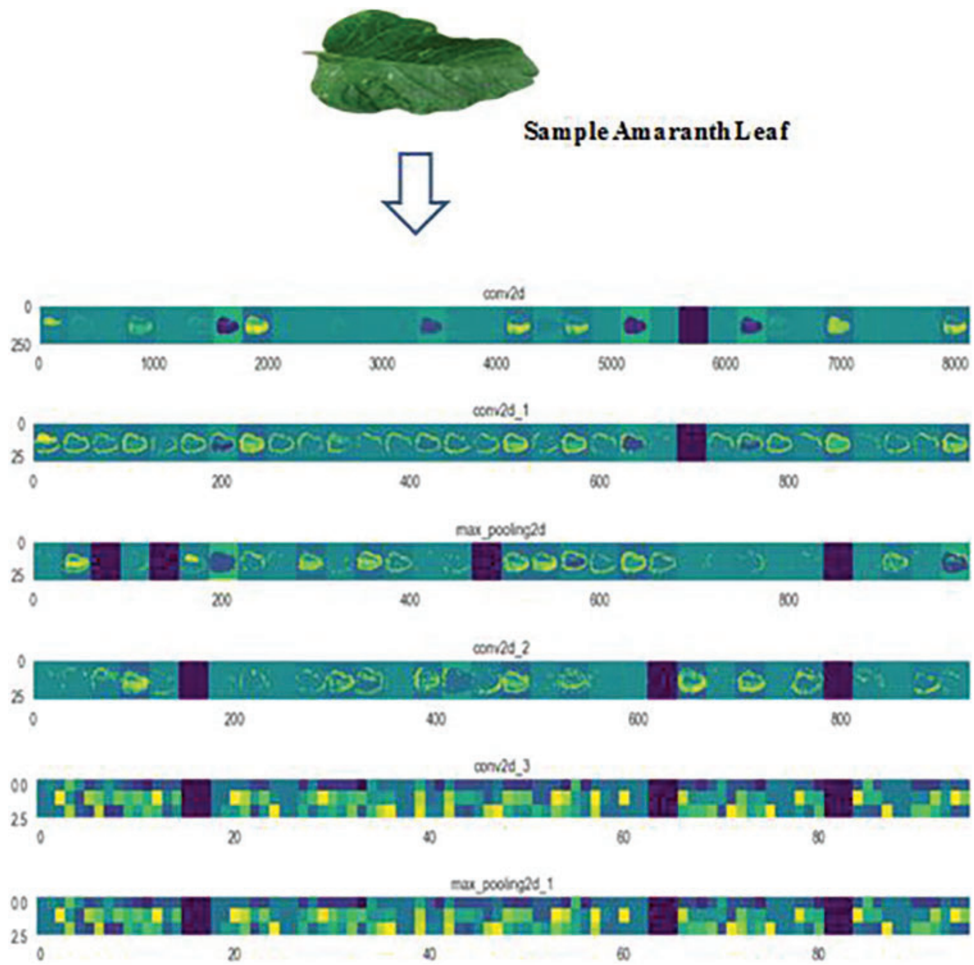

Figure 5: Sample amaranth leaf feature visualization

Finally, the proposed model classifies the spinach category accurately. Fig. 6 shows the proposed CNN architecture summary for the training model. In the proposed CNN model, the number features is extracted in the first, second, third, fourth, first dense layer, and second dense layer is 896, 9248, 9248, 9248, 73984, and 1028, respectively. Finally, the total number of parameters is 103652.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param
=================================================================
 conv2d (Conv2D)             (None, 256, 256, 32)      896

 conv2d_1 (Conv2D)           (None, 254, 254, 32)      9248

 max_pooling2d (MaxPooling2D  (None, 31, 31, 32)       0
 )

 conv2d_2 (Conv2D)           (None, 31, 31, 32)        9248

 conv2d_3 (Conv2D)           (None, 29, 29, 32)        9248

 max_pooling2d_1 (MaxPooling  (None, 3, 3, 32)         0
 2D)

 activation (Activation)     (None, 3, 3, 32)          0

 flatten (Flatten)           (None, 288)               0

 dense (Dense)               (None, 256)               73984

 dense_1 (Dense)             (None, 4)                 1028

=================================================================
Total params: 103,652
Trainable params: 103,652
Non-trainable params: 0
```

Figure 6: Proposed CNN model summary

The spinach classification algorithm is given in Algorithm 1.

Algorithm 1: Spinach classification

Input: set of input images $I_1, I_2, \ldots\ I_n$
Output: Output labels $Class_1$, $Class_2$, $Class_3$ and $Class_4$
for each spinach image I_i **do**
    Compute feature_map1 using convolution operation
    Compute feature_map2 using convolution operation with max pooling
    Compute feature_map3 using convolution operation
    Compute feature_map4 using convolution operation with max pooling
    Compute feature_map5 using fully connected layer
    Compute output $Class_i$ using softmax()
    end for
return output class

4 Result and Discussions

This section compares the performance of a novel CNN model with varied training and validation ratios.

4.1 Parameters of the Proposed CNN Architecture

Tab. 2 depicts the parameters of the proposed CNN architecture. The proposed model uses a learning rate of 0.01, activation function as softmax, epoch is 10, and batch size is 32. We varied the epoch. Finally, we set the epoch as 10.

Table 2: Comparing the performance of training and validation data

Model	Learning rate	Activation function	Epoch	Batch size
Proposed CNN	0.01	Softmax	10	32

4.2 Training and Test Data Split

The proposed CNN model is trained and tested with different ratios. We have split the training, and validation data ratios into 70:30, 80:20, and 90:10. The overall dataset contains 400 images.

Fig. 7 depicts a comparison of the findings from the training and validation data. It is observed that the training accuracy and losses and the testing accuracy and losses are similar. We varied the epoch count, and we noticed the optimal epoch count is ten, where we obtained the maximum test accuracy for the spinach dataset. Training accuracy, training loss, validation accuracy, and validation loss in data split 90:10 are 1.0000, 0.0401, 0.9074, and 0.3080, respectively. The accuracy of training, the loss of training, the accuracy of validation, and the loss of validation in data split 80:20 are 1.0000, 0.0415, 0.9375, and 0.2482, respectively. In a 70:30 split of data, the training accuracy, training loss, validation accuracy, and validation loss are 1.0000, 0.0299, 0.9762, and 0.0657, respectively. It is noted that a 90:10 training and validation data split provided an efficient result.

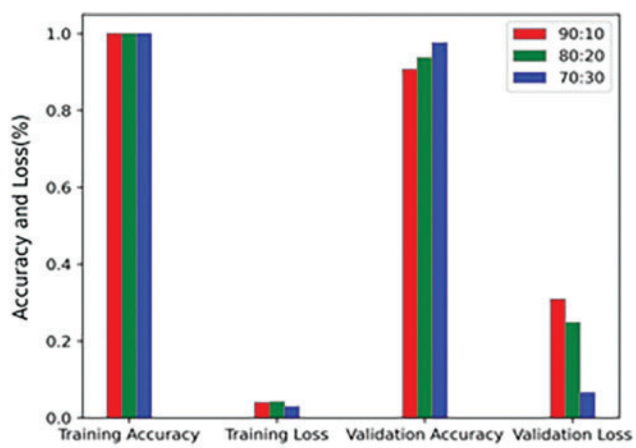

Figure 7: Comparing the performance of training and validation data

Tab. 3 compares the performance of the spinach dataset's training and validation data splits.

In parallel, Fig. 8 depicts the accuracy of training and validation with regard to epochs for a dataset divided 90:10 in terms of epochs. The training accuracy started at 42% for the 0^{th} epoch. The training accuracy has increased gradually, and it has reached 100% accuracy for the 10th epoch. The validation accuracy increased gradually, but it is always less than the train's accuracy. Finally, the validation data has reached an accuracy of 90% for the 10th epoch. In parallel, the validation or test data was tested in the proposed CNN model.

Table 3: Comparing the performance of training and validation data

Train split (%)	Validation split (%)	Training accuracy	Training loss	Validation accuracy	Validation loss
90	10	1.0000	0.0401	0.9074	0.3089
80	20	1.0000	0.0415	0.9375	0.2482
70	30	1.0000	0.0299	0.9762	0.0657

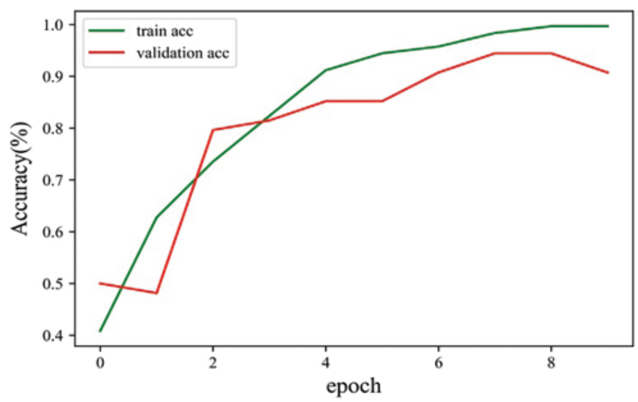

Figure 8: Training and validation accuracy *vs.* epoch

The validation or test data was tested in the proposed CNN model. The above Fig. 9 depicts the training and validation loss with regard to epochs for a dataset split 90:10 in terms of epochs. Initially, the training loss was high, but it has gradually reduced. The validation loss has decreased gradually, but it is always higher than the training accuracy.

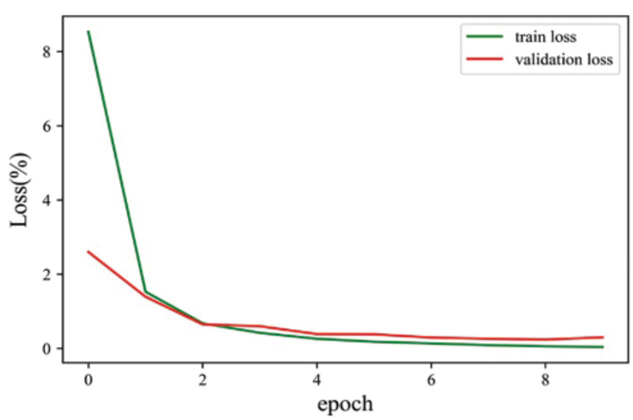

Figure 9: Training and validation accuracy *vs.* epoch

4.3 CNN Optimizer Analysis

Fig. 10 shows the optimizer analysis for the proposed CNN model. The proposed CNN model is analyzed with various optimizers, namely Adam, rmsprop, adagrid, adamax, nadam. From Fig. 8, it is observed that the Adam optimizer has provided the maximum training and validation accuracy. All the optimizers have used their default learning rate of 0.001. Thus, we have used the Adam optimizer to discuss the section further.

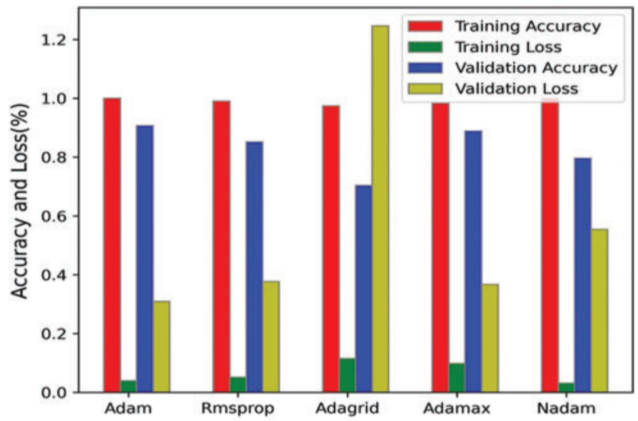

Figure 10: CNN optimizer analysis

Tab. 4 shows the proposed CNN optimizer analysis. We used various optimizers in the spinach classification. In the Tab. 4, we have provided all the training accuracy and loss values and validation accuracy and loss values for the respective optimizers.

Table 4: CNN optimizer analysis

Optimizers	Training accuracy	Training loss	Validation accuracy	Validation loss
Adam	1.0000	0.0401	0.9074	0.3089
Rmsprop	0.9902	0.0512	0.8519	0.3766
Adagrad	0.9739	0.1148	0.8889	0.3670
Adamax	0.9837	0.0983	0.888	0.3670
Nadam	1.0000	0.0311	0.7963	0.5544

4.4 Accuracy Calculation

The own spinach dataset is trained and tested with our novel CNN model. The performance of the proposed CNN is evaluated and compared using confusion matrix. A confusion matrix contains True Positive (TP), False Positive (FP), True Negative (TN) and False Negative (FN). TP and TN imply that the model predicts that all of the positive class will be positive and all of the negative class will be negative. It is possible that the model predicts wrongly from the positive class or mistakenly predicts from the negative class.

Based on the above performance metrics, we compute the Accuracy (ACC) and it is given in Eq. (7). The accuracy indicates that the model classifies the all positive class positive and all the negative class as negative.

$$ACC = \frac{TN + TP}{FP + TP + FN + TN} \tag{7}$$

Precision indicates that the model is not classify negative value as positive. Its calculation is given in Eq. (8).

$$precision = \frac{TP}{TP + FP} \tag{8}$$

Recall indicates that the model classifies all positive value as positive and its calculation is given in Eq. (9).

$$Recall = \frac{TP}{TP + FN} \tag{9}$$

The F1-score represents the average value of both accuracy and recall, and it is calculated using the formula in Eq. (10).

$$F1 - Score = \left(2 \times \left[\frac{Precision \ \times \ Recall}{Precision + Recall}\right]\right) \tag{10}$$

The confusion matrix for spinach categorization is depicted in Fig. 11. In the confusion matrix, the true labels are mentioned vertically and the predicted labels are mentioned in the horizontally.

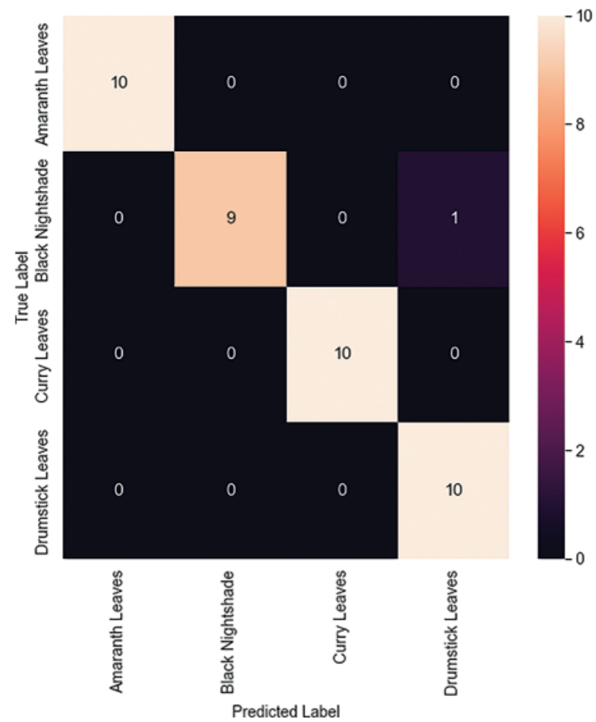

Figure 11: Confusion matrix of spinach classification

Tab. 5 shows the accuracy of spinach classification. The test data contains Amaranth leaves, Black nightshade, curry leaves and drumstick leaves. Each class of test sets has ten images. In that, we performed the fine-tuning of the proposed novel CNN model. All the images of amaranth es, curry leaves, and drumstick leaves are classified correctly. However, the class Black Nightshade has ten images correctly classified and one image misclassified. Finally, the proposed CNN model provides 97.5% accuracy. All the images of amaranth leaves, curry leaves, and drumstick leaves are classified correctly. However, the class Black Nightshade is classed correctly, and one class is misclassified.

Table 5: Accuracy of spinach classification

Classes	Amaranth leaves	Black nightshade	Curry leaves	Drumstick	Precision (%)	Recall (%)	F1-score (%)	Accuracy (%)
Amaranth leaves	10	0	0	0	100	100	100	97.5%
Black nightshade	0	9	0	1	100	90	94.7	
Curry leaves	0	0	10	0	100	100	100	
Drumstick	0	0	0	10	100	100	100	

In addition, we used the spinach dataset and performed the comparison that the accuracy of the proposed CNN is compared with various popular classification algorithms or models, namely Support Vector Machine (SVM), Random Forest, VGG16, VGG19, and ResNet50. Fig. 12 shows the various classifiers with respect to accuracy.

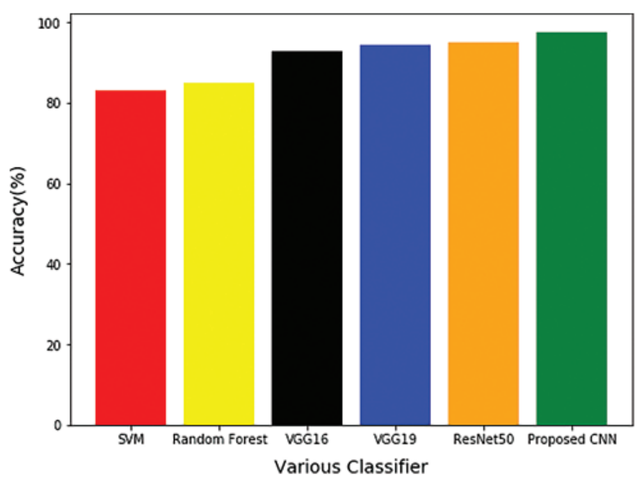

Figure 12: Various classifiers *vs.* accuracy

Tab. 6 depicts the various classifiers with respect to accuracy. The accuracy of the SVM, Random forest, VGG16, VGG19, ResNet50 and Proposed CNN are 83%, 85%, 93%, 94.5%, 95% and 97.5%, respectively.

Table 6: Various classifiers *vs.* accuracy

Classifier	Accuracy (%)
SVM	83
Random Forest	85
VGG16	93
VGG19	94.5
ResNet50	95
Proposed CNN	97.5

5 Conclusion and Future Work

Deep Learning is one of the most popular research algorithms to increase the accuracy of data analysis. Spinach recognition or classification is a challenging task due to the shape of the spinach leaves. Many researchers have presented various machine learning and deep learning techniques to categories plant images more reliably in recent years. This paper proposed a novel CNN to recognize spinach more accurately. The proposed CNN has achieved 97.5% overall classification accuracy. It is observed that the proposed CNN model extracts various features like color, shape, edges appropriately in the spinach dataset. The proposed CNN architecture is classified into four classes: Amaranth leaves, Black nightshade, Curry leaves, and Drumstick leaves. Furthermore, the proposed CNN is compared with the popular classifiers, namely SVM, Random Forest, VGG 16, VGG19 and ResNet50. The accuracy of proposed CNN provides superior than SVM, Random Forest, VGG 16, VGG19 and ResNet50.

In future work, we plan to prepare a dataset with all the spinach available in India. In addition, we planned to implement the framework to recognize all kinds of spinaches using an effective ensemble CNN model.

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