Date of publication JUN-30, 2023, date of current version JAN-31, 2023.
www.computingonline.net / computing@computingonline.net

Print ISSN 1727-6209
Online ISSN 2312-5381
DOI 10.47839/ijc.22.2.3088

Severity Stage Identification and Pest Detection of Tomato Disease Using Deep Learning

PROTHAMA SARDAR, ROMANA RAHMAN EMA, SK. SHALAUDDIN KABIR, MD. NASIM ADNAN, SYED MD. GALIB

Department of Computer Science and Engineering, Jashore University of Science and Technology, Jashore-7408, Bangladesh

Corresponding author: Romana Rahman Ema (e-mail: rr.ema@just.edu.bd).

ABSTRACT In Bangladesh, most people depend on agriculture for their livelihood. The country's economy and agricultural production are hampered if plants are affected by diseases. Crop pests also disrupt agricultural production. So, this paper proposes leaf disease, disease severity stage, and pest detection strategies with suggestions for prevention strategies using five notable Convolutional Neural Network models (CNN) such as VGG16, Resnet50, AlexNet, EfficientNetB2, and EfficientNetB3. This paper uses a dataset of tomato leaves consisting of 41,763 images which cover 10 classes of tomato disease, and a dataset of pests consisting of 4,271 images which cover 8 classes of pests. Firstly, these models are used for the classification of diseases and pests. Then disease and pest prevention techniques are shown. For disease and pest detection, EfficientNetB3 gives the best accuracy for training (99.85%), (99.80%), and validation (97.85%), (97.45%) respectively. For severity stage identification, AlexNet gives the best accuracy for training (69.02%) and validation (72.49%).

KEYWORDS deep learning; prevention strategies; severity stage identification; disease detection; pest detection.

I. INTRODUCTION

Along with the economic growth of any country, the country's GDP also depends on agriculture [1]. So, agriculture is considered one of the world's most important occupations. Like other countries, the main occupation of people in Bangladesh is agriculture. But farmers in our country are facing losses due to foliar diseases and insect attacks which reduce crop productivity. Along with the increase in population, the demand for food is also increasing. Therefore, disease detection and pest identification are essential for good yield [2]. Accurate detection of diseases at an early stage is helpful in reducing losses in agriculture [3].

There are many methods of diagnosing plant disease. Many farmers diagnose the disease using these methods on the advice of experts. But for specialist consultation, collecting samples and taking them to the lab for diagnosis is expensive and time-consuming. So, digitalized methods of crop disease detection need to be invented [4]. For this purpose, deep learning such as convolutional neural network is more useful which takes an image as an input and gives the predicted result as output depending on various features in less time.

Different crop diseases have different colors, shapes, and sizes which are considered features. These features are used to identify diseases [5]. Although the color of many diseases may be the same other features can be detected by our proposed model which helps to identify the diseases accurately.

Tomato is considered one of the most popular vegetables which are eaten as a salad, served as a cooked vegetable, and various dishes, pickled, and sauces are prepared with tomato. Tomatoes are riched in Vitamin C, beta-carotene, and Vitamin E which are the main antioxidants. Besides potassium is also present in it [6]. But tomatoes are attacked by various diseases and pests which reduce tomato production. So, to identify tomato disease and pest alternative to a manual identification process digitalized process is proposed in this paper.

The proposed methodology consists of four major steps: data acquisition, pre-processing, feature extraction and classification, and suggest prevention technique. Datasets have been collected from Kaggle to implement the proposed method. Data is resized, rescaled, zoomed, horizontally flipped, and sheared in the pre-processing step. Then the images are fed into the classification model. For feature extraction and classification VGG16, Resnet50, AlexNet, EfficientNetB2, and EfficientNetB7 have been used [6].

The rest of the paper is organized as follows: section 2 describes the related work done in the previous year, section 3 describes the preliminaries, section 4 represents the proposed methodology, section 5 describes the result and discussion, and section 6 is the conclusion. The overall research process is shown in Fig. 1.

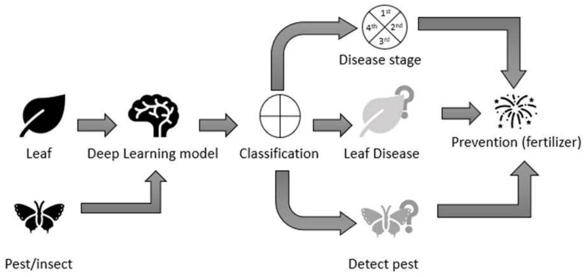


Figure 1. Tomato leaf disease and pest detection

II. RELATED WORKS

Various CNN models are shown in this paper for classifying tomato leaf disease, tomato pest, and tomato bacterial spots at different stages. Previous also different CNN model is used to classify leaf disease. This section describes the different process of previous work that is used for the classification of leaf disease and pest detection.

Omkar Kulkarni [5] proposed a deep-learning-based model to identify crop diseases. They used the PlantVillage dataset which is a public dataset. InceptionV3 and MobileNet are used from different deep-learning-based models to identify crop diseases in this paper. 5277 images of 5 different types of crops are used to fine-tune these models. 99.62% and 99.74% accuracy are achieved by InceptionV3 and MobileNet models respectively.

Prajwala TM et al. [6] experimented AlexNet, GoogleNet, and LeNet models architecture for tomato leaf disease detection. But LeNet which is the variation of a convolutional neural model was given the best accuracy. From the PlantVillage dataset, 10 different classes of tomato leaf disease images are used in this paper. These images are resized into 60 × 60 resolution in pre-processing phase. For feature extraction convolutional and max pooling layers are used and for classification, the fully connected layer is used. 94-95% accuracy was achieved by the proposed model.

Husnul Ajra et al. [7] used 4000 images of Potato early blight, Tomato early blight, Potato late blight, and Tomato late blight to classify and give a graphical layout of a preventive measurement for identified disease. Also, 2000 healthy images are used in this paper. By using 2 CNN models ResNet50 and AlexNet, at first healthy and unhealthy leaves are classified then these unhealthy leaves are classified into four different leaf diseases and also give preventive measures for this detected disease. 97% and 96.1% accuracy of ResNet50 and 96.5% and 95.3% accuracy of AlexNet is achieved for the detection of healthy-unhealthy and four different leaf diseases, respectively.

Chowdhury R. Rahman et al. [8] collected 1426 images of eight different rice pests and diseases from paddy fields of Bangladesh Rice Research Institute (BRRI) for rice pest and leaf disease detection. Baseline training, Fine Tuning, and Transfer learning approaches are applied on VGG16, InceptionV3, MobileNetV2, NasNet Mobile, SqueezeNetV1.1, and Simple CNN for this purpose. VGG16 and InceptioV3 are State-of-the-art large-scale architectures that are fine-tuned for detecting rice diseases and pest detection. For mobile devices, MobileNetV2, NasNet Mobile, and SqueezeNetV1.1 were proposed. The fine-tuning method gives the best accuracy for all these models. The best accuracy of 97.12% is achieved by fine-tuned VGG16.

Divyansh Tiwari et al. [9] utilized 2152 images of potato late blight, potato healthy, and potato early blight images from the PlantVillage dataset. For feature extraction VGG16, VGG19, and Inceptiov3 are used as well as for classification SVM, KNN, neural network, and logistic regression are used. Along with VGG16 logistic regression gave the best accuracy of 97.8%.

Ebrahim Hirani et al. [4] used CNN, transfer learning, and Visual transformers approach for plant disease detection. In CNN, different filters are used in the convolutional layer, and the 'relu' activation function is used in the fully connected layer to reduce overfitting dropout. In transfer learning, the InceptioV3 model is used. In visual transformer approaches STN (Small Transformer Network) and LTN (Large Transformer Network) are used. The LTN achieved the best validation accuracy of 97.98%.

Although plant disease detection and rarely insect detection have been done in the past, disease detection alone is not a good solution for increasing crop production. A prevention strategy with this detection is more effective. The achievement of this paper is to identify 10 different diseases and 8 different pests of tomatoes and provide a preventive solution for each disease and pest that is more helpful for farmers. Identifying stage-wise tomato bacterial spots and providing solutions for each stage is another achievement of this paper.

III. PRELIMINARIES

A. TOMATO

Among different types of vegetables, tomato is the most popular vegetable across the world. So agricultural development depends on the production of tomatoes [10]. Vitamin C, folate, and potassium are present in tomatoes. Tomatoes contain more carotenoids than phytonutrients. The most important carotenoid in tomatoes is lycopene, as well as other carotenoids, including gamma-carotene, beta-carotene, and phytoene also present. Besides vitamin E, flavonoids, trace elements, phytosterols, and different water-soluble vitamins are also present in tomatoes [11]. But tomato leaves are attacked by various diseases and pests which destroy the production of tomatoes.

B. TOMATO LEAF DISEASE

Tomato leaf disease impacts the growth and production of tomatoes. As a result, farmer faces economic problems [12]. Leaf diseases are caused by various pathogens such as viruses, fungi, bacteria, and pests. As a result, foliar diseases and insect attacks cause 10% to 25% crop loss every year and farmers suffer huge economic losses as income depends on the number of healthy crops they produce. So, overcoming this problem is a big challenge. So, by detecting leaf diseases and pests through an automated system we can help the farmer to overcome this challenge [13]. Tomato leaves are attacked by nine common diseases. Bacterial-borne diseases are Tomato Bacterial Spots. Fungi-borne diseases are Tomato Early Blight, Tomato Late Blight, Tomato Leaf Mold, Tomato Septoria leaf spot, and Tomato Target Spot. Virus-borne diseases are the Tomato Mosaic virus, and Tomato Yellow Leaf Curl Virus. Pest-affected diseases are Tomato Spider mites [15]. Nine different tomato leaf diseases and pathogens of this disease are shown in Fig. 2 and Table 1.

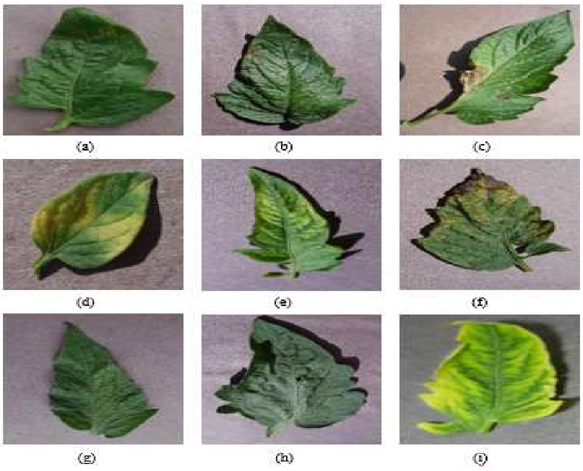


Figure 2. (a) Tomato Bacterial Spot, (b) Tomato Early Blight, (c) Tomato Late Blight, (d) Tomato Leaf Mold, (e) Tomato Mosaic Virus, (f) Tomato Septoria Leaf Spot, (g) Tomato Spider Mites, (h) Tomato Target Spot, (i) Tomato Yellow Leaf Curl Virus [15]

Table 1. Pathogen of Tomato Leaf Disease

Disease Name	Pathogen
Tomato Bacterial Spot	Xanthomonas vesicatoria
Tomato Early Blight	Alternaria solani
Tomato Late Blight	Phytophthora infestans
Tomato Leaf Mold	Pseudocercospora fuligena
Tomato Mosaic Virus	Tomato Mosaic Virus
Tomato Septoria leaf spot	Septoria lycopersici
Tomato Spider Mites	Tomato Spider Mites
Tomato Target Spot	Corynespora cassiicola
Tomato Yellow Leaf Curl	Tomato yellow leaf curl virus

C. TOMATO PEST

Various pest affects tomato and decreases their growth. So, to increase production identification of tomato pests is essential [16]. Tomato leaves and tomatoes are attacked by various types of pests. The most common types of pests are Tetranychus urticae, Bemisia argentifolii, Zeugodacus cucurbitae, Thrips palmi, Myzus persicae, Spodoptera litura, Spodoptera exigua, and Helicoverpa armigera. Eight different pests are shown in Fig. 3.

Figure 3. (a) Bemisia argentifolii, (b) Helicoverpa armigera, (c) Myzus persicae, (d) Spodoptera exigua, (e) Spodoptera litura, (f) Tetranychus urticae, (g) Thrips palmi, (h) Zeugodacus cucurbitae [17]

D. TOMATO BACTERIAL SPOT STAGE

Tomato Bacterial Spot is caused by bacteria. Tomato production is disrupted due to bacteria. Each Disease has different stages. Usually, the last stage of any disease is more serious than the first stage. So, stage identification is required to reduce intensity. Because if its severity is identified, the disease can be reduced by taking proper measures at the early stage. Tomato bacterial spot is classified into five stages depending on disease radiation percentage. Five stages of tomato bacterial spot and tomato healthy leaf images are shown in Fig. 4.

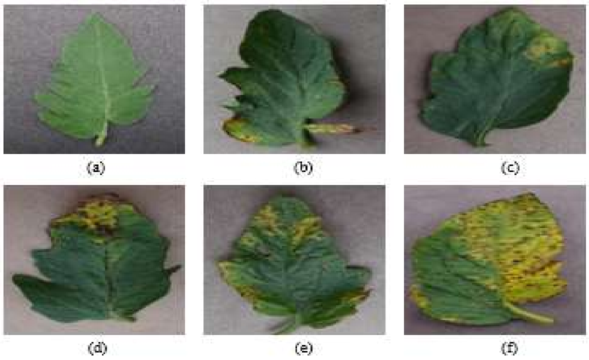


Figure 4. (a) Tomato Healthy, (b) 1st Stage, (c) 2nd Stage, (d) 3rd Stage, (e) 4th Stage, (f) 5th Stage [15]

IV. PROPOSED METHODOLOGY

For image classification, the Convolutional neural network is regarded as the most competent. To solve the limitations of previous work five notable CNN model is proposed in this paper. The proposed flowchart is shown in Fig. 5.

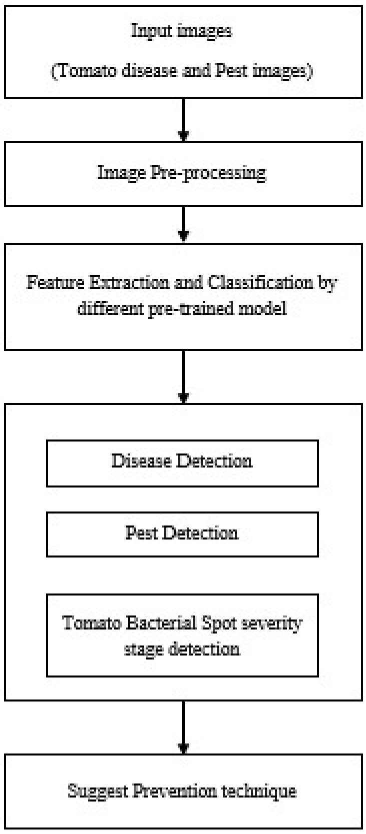


Figure 5. Proposed flowchart

The flowchart proposed in Fig. 5 consists of four following phases:

- The first phase is the input image phase where tomato leaf and pest images are taken from open-source Kaggle and Mendeley Data.
- The second phase is the image pre-processing phase where various dimensions of images are resized into a suitable form.
- The next phase is the feature extraction and classification phase where five classification models such as EfficientNetB3, EfficientNetB2, VGG16, AlexNet, and ResNet50 are used to extract features and identify diseases and pests.
- The last phase is given a suggestion of tomato leaf disease and pests.

Now the proposed phases are described step by step in detail below:

A. TOMATO LEAF AND PEST IMAGE DATASET

In this paper, PlantifyDr Dataset [15] is used for disease detection, which is available on Kaggle. This dataset contains 1,25,000 images of 10 different plants and the number of plant diseases is 37. The tomato plant from this dataset contains 41,763 images of 10 different diseases that are used to classify diseases. At first, the dataset is split into two parts: the training part contains 37,582 images (90%) and the validation part contains 4,181 images (10%). Then from the training part, 3759 images (10%) are used for testing purposes.

For pest detection, the tomato pest dataset is used which is available on Mendeley Data [17]. This dataset contains 4,271 images of 8 different pests of tomato. At first, the dataset is split into two parts: the training part contains 3,456 images (70%) and the validation part contains 431 images (30%). Then from the training part, 384 images (10%) are used for testing purposes.

For stage-wise prevention technique suggestion, from PlantifyDr Dataset Tomato Bacterial Spot is taken which contains 4,355 images. From these images, 882 images are categorized into 5 stages (1st stage,2nd stage, 3rd stage, 4th stage, and 5th stage) depending on 5 features that are suggested by a pathologist which is shown in Table 2 [18]. Then the dataset is split into two parts: the training part contains 1,117 images (70%) and the validation part contains 538 images (30%). Then from the training part, 125 images (10%) are used for testing purposes. 5 features are:

Table 2. Severity Stage of Tomato Bacterial Spot

Stage	Spot area in Percentage	Description
Healthy Leaf	0%	Leaf free from the spot.
1st stage	0-5%	0-5% of the leaf area is affected by spots.
2nd stage	6-20%	6-20% of the leaf area is affected by spots.
3rd stage	21-40%	21-40% of the leaf area is affected by spots.
4th stage	41-70%	41-70% of the leaf area is affected by spots.
5th stage	>70%	>70% of the leaf area is affected by spots.

Table 2 shows the severity stage of tomato bacterial spots. If 0-5%, 6-20%, 21-40%, 41-70%, or more than 70% of the leaf area is affected by spots, the severity stage will be 1st, 2nd, 3rd, 4th, or 5th respectively. If the leaf is free from the spot is called a healthy leaf.

B. IMAGE PRE-PROCESSING

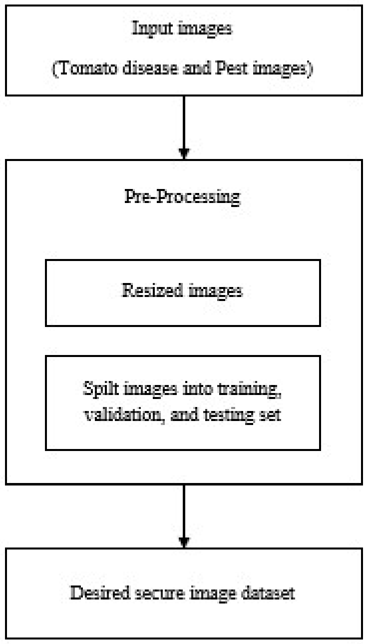


Figure 6. Pre-processing

The next phase is the image pre-processing phase which is shown in Fig. 6. Image pre-processing is used for preparing images into a desirable format to feed into the model. By image pre-processing technique raw images can be converted into desirable images with high quality. The dataset that is used in this proposed system is random-sized tomato leaf and pest images, as well as the dataset, is not split into training, validation, and testing set. The pre-processing technique's different phases that are applied to the proposed system are shown in Fig. 6. In the first phase, the images are resized into a suitable form. Then these resized images are split into training, validation, and testing sets. Finally, pre-processing technique gave the desired secure image datasets to classify tomato leaf disease, tomato pest, and tomato Bacterial Spot severity stage.

C. FEATURE EXTRACTION AND CLASSIFICATION

After pre-processing the images next phase is to extract features from the images so that the images can be classified depending on these features. For feature extraction and classification, transfer learning approaches are used in this paper. Classification of tomato leaf disease, tomato pest as well as stage-wise tomato bacterial spot detection is the main motive of this paper. Different transfer learning models such as EfficientNetB3, VGG16, ResNet50, AlexNet, and EfficientNetB2 are used to identify the disease and pest. Classification means categorizing the images or objects depending on the predetermined categories. Pre-trained models are:

1) EfficientNet

The main objective of deep neural networks is to achieve optimal accuracy with a small model. The EfficientNet model is considered a state-of-the-art model because in 2019 it achieved 84.4% and 97.1% as top-1 and top-5 accuracies, respectively, on the ImageNet dataset with fewer parameters.

B0-B7 are eight models of EfficientNet. The Leaky ReLu activation function is used in the EfficientNet model instead of the Rectifier Linear Unit (ReLu). The EfficientNet architecture produces an efficient result by using a composite coefficient to scale the depth, width, and resolution of the network equally. Bottleneck convolutional layer is used in the EfficientNet model which is first used in MobileNetV2 architecture. Compare to other models, EfficientNet requires less computation by f^2 factor where f is the kernel size [15,20]. EfficientNetB2 and EfficientNetB3 models are used in this research which architecture and modules are shown in Fig. 7, Fig. 8, and Fig. 9.

Algorithm of EfficientNetB2 and EfficientNetB3:

Input: Tomato leaf disease and pest image
Output: Classification of disease and pest
Procedure:
1. Follow steps 2 to 5 for a training and validation dataset.
2. change the size to (256 × 256)
3. resize the image in pre-processing (224 × 224)
4. If a set is (224 × 224)
5. pre-processing image with different pre-processing techniques
6.training EfficientNet_model = EfficientNetB2/EfficientNetB3
7. for a Model in EfficientNet_model
8. fined tuned with transfer learning
9. for epochs = 50.
10. Set the learning rate to 0.001 using steps 11 to 12
11. for images in tomato leaf disease and pest images:
12. update Model parameter
13. end step 11’s for loop
14. if the loss is not reduced for 2 epochs, follow steps 15 to 16
15. then: use ReduceLROnPlateau callbacks
16. decrease learning rate
17. if the loss is not reduced for 4 epochs
18. then: use EarlyStopping callbacks
19. return model accuracy
20. end step 9’s for loop
21. end step 7’s for loop

2) AlexNet

Fig. 10 shows the AlexNet architecture consisting of eight layers, with five convolutional layers and three fully connected layers. The first convolutional layer consists of 96 filters and (11×11) kernels for feature extraction, and then a 3×3 MaxPooling layer is added to reduce the size of thefeature map. The second convolutional layer is the same as the first convolutional layer but contains 256 filters and (5×5) kernels. The third, fourth, and fifth convolutional layers have 384, 384, and 256 filters and (3×3) kernels respectively. A 6×6 MaxPooling layer is then added to reduce the size of the feature map by the convolutional layer. A fully connected layer is added to transform the features into one-dimensional vectors. Among the three fully connected layers, two fully connected layers use the ReLu activation function. Finally, a fully connected layer is used as the output layer and the SoftMax activation function is added for prediction [21].

Algorithm of AlexNet:
Input: Tomato leaf disease and pest image
Output: Classification of disease and pest
Procedure:
1. Follow steps 2 to 5 for a training and validation dataset.
2. change the size to (256 × 256)
3. resize the image in pre-processing (224 × 224)
4. If a set is (224 × 224)
5. pre-processing image with different pre-processing techniques
6.AlexNet_model = AlexNet ()
7. layer1 ⟵ Conv2D, MaxPooling2D
8. layer2 ⟵ Conv2D, MaxPooling2D
9. layer3-5 ⟵ Conv2D, Conv2D, Conv2D, MaxPooling2D
10. layer6-8 ⟵ Fully Connected layer
11. training AlexNet_model
12. for epochs = 50.
13. Set the learning rate to 0.001 using steps 11 to 12
14. for images in tomato leaf disease and pest images:
15. update AlexNet_model parameter
16. end step 11’s for loop
17. if the loss is not reduced for 2 epochs, follow steps 15 to 16
18. then: use ReduceLROnPlateau callbacks
19. decrease learning rate
20. if the loss is not reduced for 4 epochs
21. then: use EarlyStopping callbacks
22. return model accuracy
23. end step 9’s for loop

3) VGG16

In Fig. 11 shows VGG16 architecture which consists of sixteen layers with thirteen convolutional and three fully connected layers. 3×3 and 2×2 kernels are used in the convolutional and pooling layer respectively. VGG16 has five blocks. Each block consists of multiple convolutional layers and one pooling layer. The pooling layer is used to reduce the feature map size. In block-1 and block-2 has two convolutional layers with 64 and 128 filters for feature extraction and one pooling layer for reducing the feature map size. Similarly, block-3, block-4, and block-5 have three convolutional layers with various filters for feature extraction and one pooling layer for reducing the feature map size. Among three fully connected layers, two fully connected layers used ReLu activation functions. At last, one fully connected layer is used as the output layer and the SoftMax activation function is added for predictions [21].

Algorithm of VGG16:
Input: Tomato leaf disease and pest image
Output: Classification of disease and pest
Procedure:
1. Follow steps 2 to 5 for a training and validation dataset.
2. change the size to (256 × 256)
3. resize the image in pre-processing (224 × 224)
4. If a set is (224 × 224)
5. pre-processing image with different pre-processing techniques
6. VGG16_model = VGG16 ()
7. layer1 ⟵ Conv2D, Conv2D, MaxPooling2D
8. layer2 ⟵ Conv2D, Conv2D, MaxPooling2D

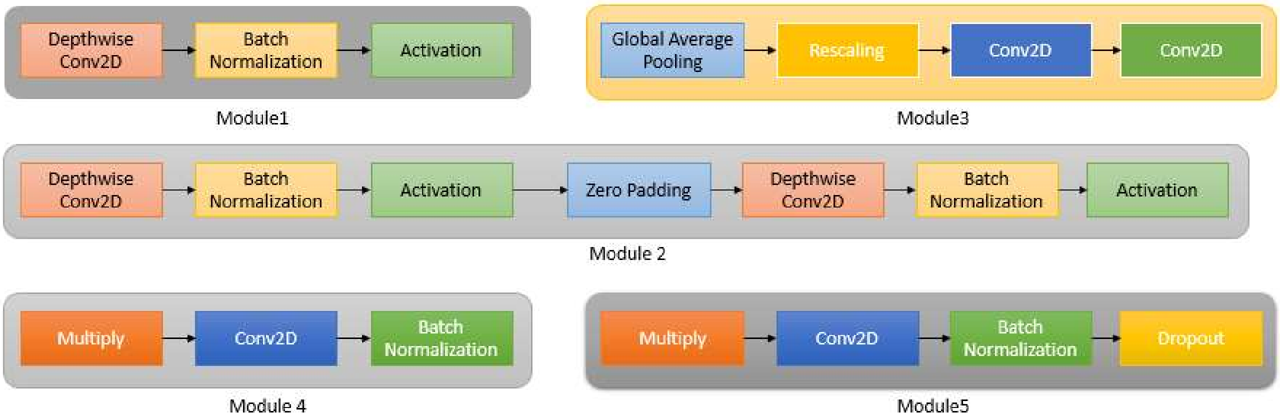


Figure 7. 5 modules [20]

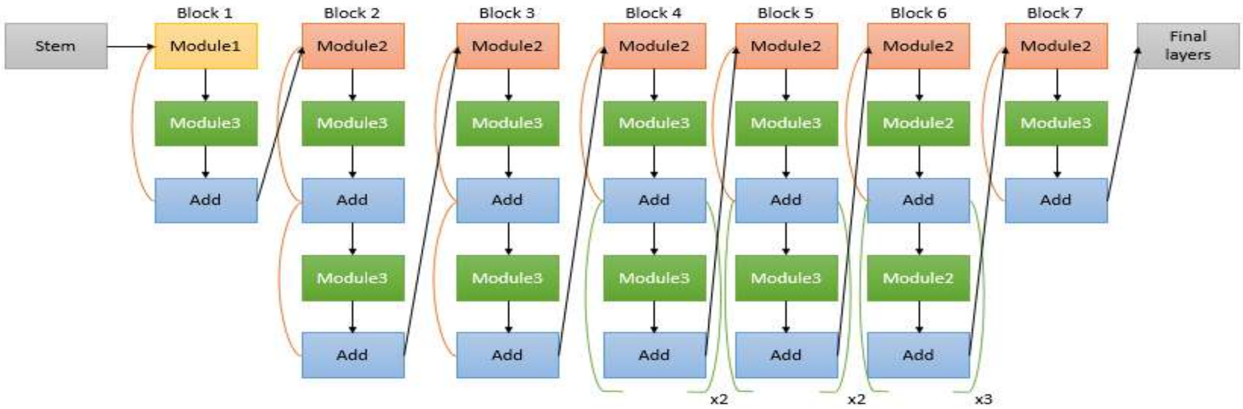


Figure 8. EfficientNetB2 [20]

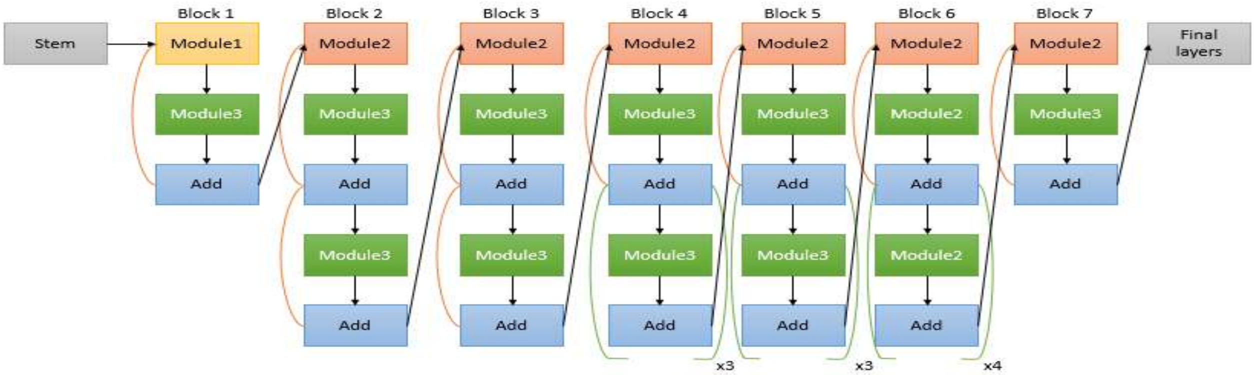


Figure 9. EfficientNetB3 [20]

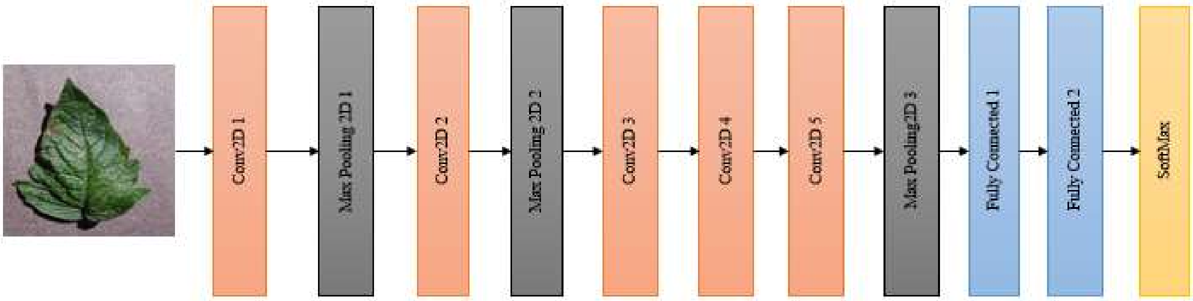


Figure 10. AlexNet [21,22]

9. layer3 ← Conv2D, Conv2D, Conv2D, MaxPooling2D
9. layer4 ← Conv2D, Conv2D, Conv2D, MaxPooling2D
9. layer5 ← Conv2D, Conv2D, Conv2D, MaxPooling2D
10. layer 14-16 ← Fully Connected layer
11. training AlexNet_model
12. for epochs = 50.
13. Set the learning rate to 0.001 using steps 11 to 12
14. for images in tomato leaf disease and pest images:
15. update VGG16_model parameter
16. end step 11's for loop
17. if the loss is not reduced for 2 epochs, follow steps 15 to 16
18. then: use ReduceLROnPlateau callbacks
19. decrease learning rate
20. if the loss is not reduced for 4 epochs
21. then: use EarlyStopping callbacks
22. return model accuracy
23. end step 9's for loop

4) ResNet50

The architecture of ResNet50 has 50 layers which are shown in Fig. 15. The vanishing gradient problem is a notable problem of convolutional neural networks. The vanishing gradient problem means that during backpropagation when the gradient value decreases, then a slight change in weights occurs. In ResNet50 skip, the connection is used to control this problem which is shown in Fig. 12. Without a skip connection output is:

$$F\ (w*x + b) = F(x) \qquad (1)$$

With a skip connection output is:

$$F(x) + x$$

Along with this vanishing gradient problem, optimization of the network and degradation problem is found in CNN which is also solved by the ResNet50 model.[24] Two types of blocks are used in the ResNet50 model such as identity block and the convolutional block is shown in Fig. 13 and Fig. 14 respectively. Identity block means x is added to the output layer if the input size is equal to the output size. To build the input size and output size equal a convolutional block is added in the shortcut path [25].

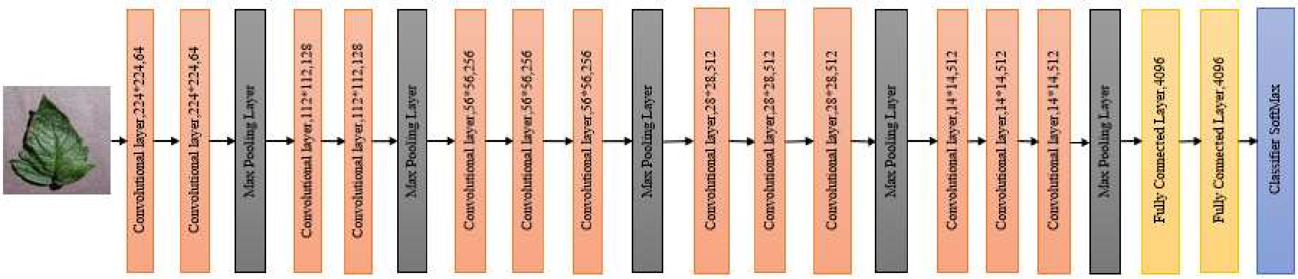


Figure 11. VGG16 architecture [21,23]

Algorithm of ResNet50:

Input: Tomato leaf disease and pest image
Output: Classification of disease and pest
Procedure:
1. Follow steps 2 to 5 for a training and validation dataset.
2. change the size to (256 × 256)
3. resize the image in pre-processing (224 × 224)
4. If a set is (224 × 224)
5. pre-processing image with different pre-processing techniques
6.training ResNet50_model = ResNet50
7. for a Model in ResNet50_model
8. fined tuned with transfer learning
9. for epochs = 50.
10. Set the learning rate to 0.001 using steps 11 to 12
11. for images in tomato leaf disease and pest images:
12. update model parameter
13. end step 11's for loop
14. if the loss is not reduced for 2 epochs, follow steps 15 to 16
15. then: use ReduceLROnPlateau callbacks
16. decrease learning rate
17. if the loss is not reduced for 4 epochs
18. then: use EarlyStopping callbacks
19. return model accuracy
20. end step 9's for loop
21. end step 7's for loop [16]

D) SUGGEST PREVENTION TECHNIQUE

The other motive of this paper is to give suggestions for a preventive technique for tomato leaf disease, and tomato pests and also suggest step-wise prevention ways of Tomato Bacterial spots. So that farmers can be befitted for reducing the effect of tomatoes' different diseases and pests. After classifying tomato disease, tomato pest, and different stages of tomato bacterial spot, the prevention technique is suggested by using the EfficientNetB7, VGG16, ResNet50, AlexNet, and EfficientNetB2 models.

V. RESULT AND DISCUSSION

To analyze the best result for tomato leaf disease detection, tomato pest detection, and tomato bacterial spot severity stages detection, a comparison among 5 different classification models' training, validation and testing accuracy has been drawn in Fig. 16. Fig. 16(a), there is shown a comparison among 5 classification models' training accuracy for tomato leaf disease detection, tomato pest detection, and tomato bacterial spot severity stages detection. Fig. 16(b), there is

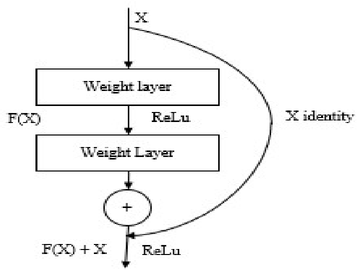


Figure 12. Skip connection [25]

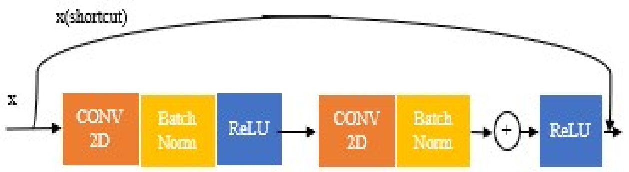


Figure 13. Identity Block [25]

After applying different classification models such as EfficientNetB3, VGG16, ResNet50, AlexNet, and EfficientNetB2 for classifying tomato leaf disease, tomato pest, and tomato bacterial spot severity stages detection, suggest prevention techniques (Organic Control and Chemical control) that help the farmer to take proper steps for disease severity control. Organic and chemical control for leaf disease, tomato pest, and tomato Bacterial Spot Severity stages detection is

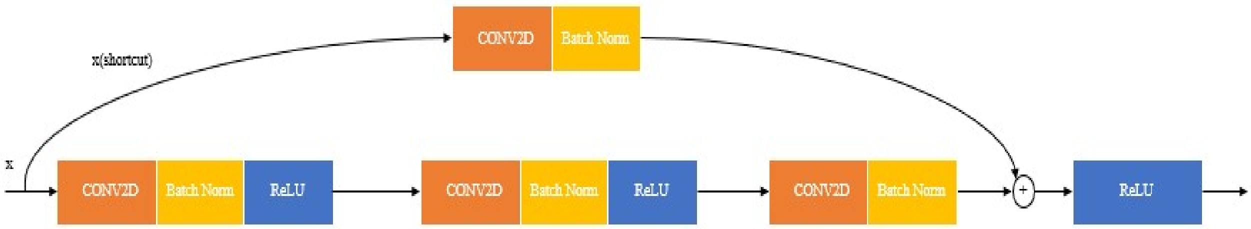


Figure 14. Convolutional Block [25]

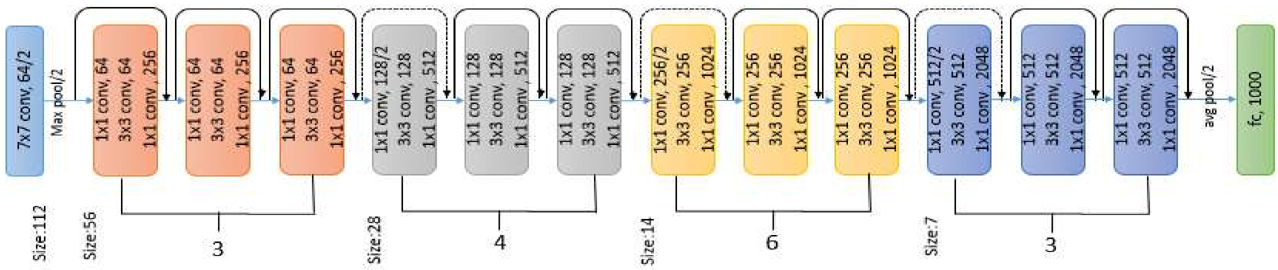
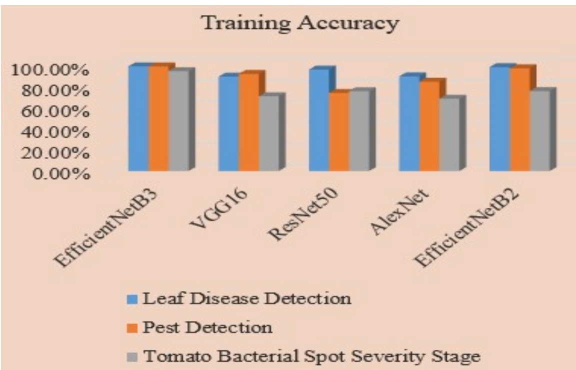


Figure 15. ResNet50 Architecture [25]

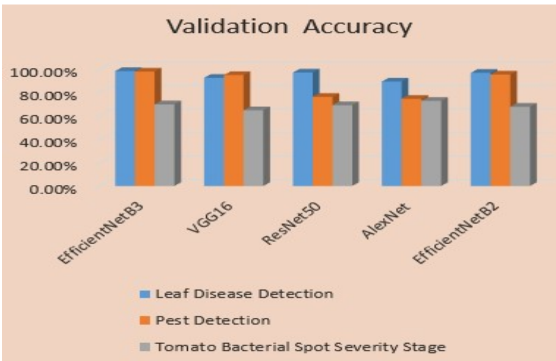
shown a comparison among 5 classification models' validation accuracy for tomato leaf disease detection, tomato pest detection, and tomato bacterial spot severity stages detection. Fig. 16(c), there is shown a comparison among 5 classification models' testing accuracy for tomato leaf disease detection, tomato pest detection, and tomato bacterial spot severity stages detection. From the analysis of Fig. 16(a), (b), and (c), it is shown that for tomato leaf disease detection EfficientNetB3 is given the best training (99.85%), validation (97.85%), and testing (96.33%) accuracy. On the other hand, for tomato pest detection also EfficientNetB3 is given the best training (99.80%), validation (97.45%), and testing (98.70%) accuracy. As well as for tomato bacterial spot severity stages detection AlexNet is given the best training (69.02%), validation (72.49%), and testing (71.20%) accuracy.



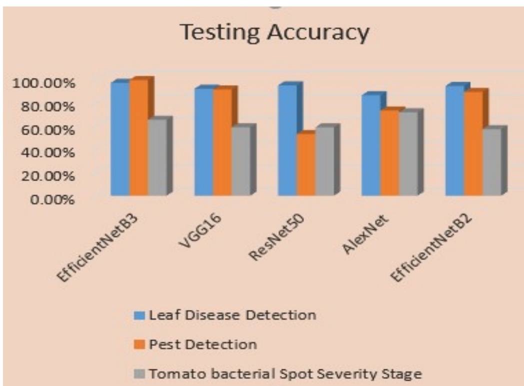
(a)

For prevention techniques:

shown in Fig. 17. In Fig. 17's left side, there is shown the



(b)



(c)

Figure 16. (a) Training Accuracy (b) Validation accuracy (c) Testing Accuracy

tomato disease name also suggests organic as well as chemical control for the given input image of the disease. In Fig. 17's middle side, there is shown the tomato pest name also suggests organic as well as chemical control for the given input image of the pest. In Fig. 17's right side, there is shown the tomato Bacterial Spot Severity Stages also suggest organic as well as chemical control for the given input image of the Tomato Bacterial Spot.

Table 3. Accuracy table

Proposed Work	Model	Training	Validation	Testing
Leaf Disease Detection	EfficientNetB3	99.85%	97.85%	96.33%
	VGG16	90.08%	92.11%	91.33%
	ResNet50	96.75%	96.63%	94.20%
	AlexNet	90.30%	88.95%	85.77%
	EfficientNetB2	99.15%	96.36%	93.67%
Pest Detection	EfficientNetB3	99.80%	97.45%	98.70%
	VGG16	92.66%	94.43%	90.62%
	ResNet50	74.49%	75.87%	52.60%
	AlexNet	85.19%	74.25%	72.66%
	EfficientNetB2	97.98%	94.90%	88.54%
Tomato Bacterial Spot Severity stages	EfficientNetB3	95.34%	69.52%	64.80%
	VGG16	71.35%	64.50%	58.40%
	ResNet50	76.19%	68.77%	58.40%
	AlexNet	69.02%	72.49%	71.20%
	EfficientNetB2	76.28%	67.47%	56.80%

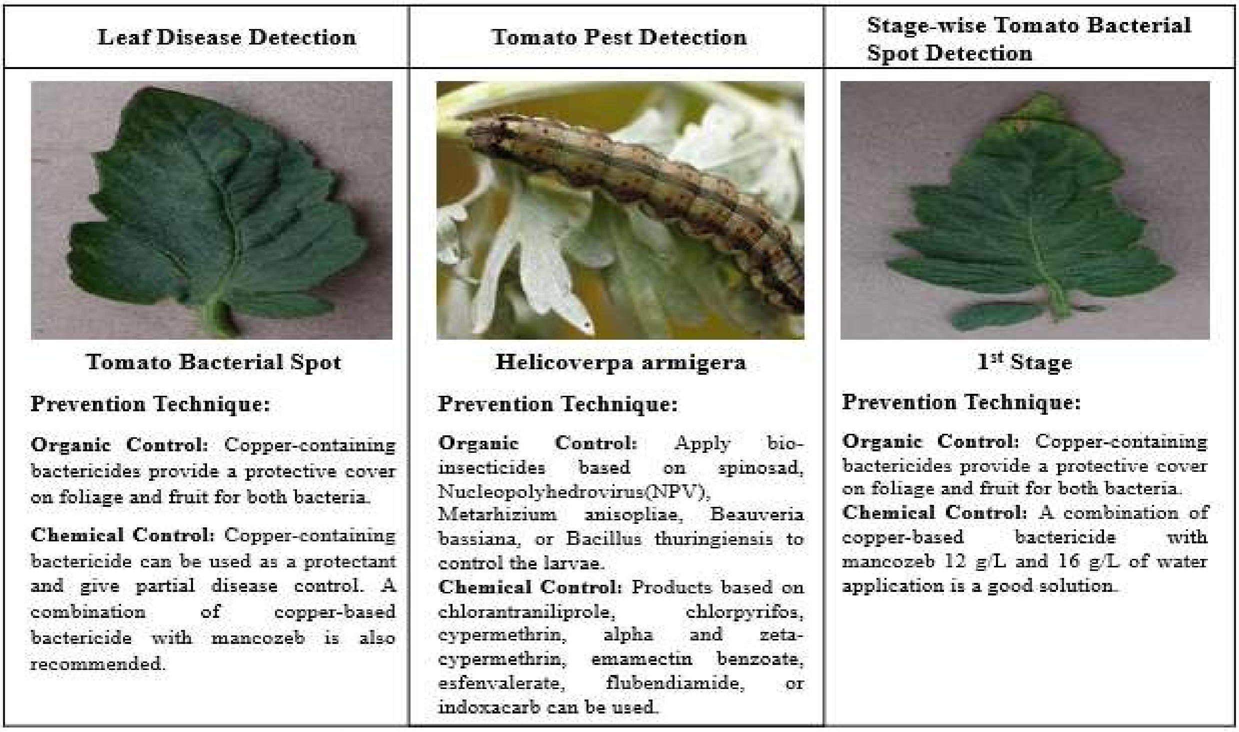


Figure 17. Suggest prevention technique

VI. CONCLUSIONS

Various problems of agriculture are mentioned in this research paper. This problem has disrupted the agricultural sector economically. So, given the importance of agriculture, the accurate detection of plant diseases and pests is very important. For this purpose, ten categories of tomato leaf diseases and eight categories of tomato pests are considered. Not only is a foliar disease and pest detection a good method to increase crop productivity, but this disease prevention strategy is the most effective. In this paper, these detections are done by using five convolutional neural network models and suggest prevention techniques for each disease and pest. Among the five models for disease and pest, detection EfficientNetB3 gives the best accuracy for training (99.85%), (99.80%), and validation (97.85%), (97.45%) respectively. In the future, we aim to identify diseases and pests with a large dataset of various types of plants and pests. We thank you in advance for supplying carefully prepared camera-ready papers, which can be sent for publication without modification.

References

[1] P. Sharma, P. Hans, and S. C. Gupta, "Classification of plant leaf diseases using machine learning and image preprocessing techniques," *Proceedings of the 2020 10th International Conference on Cloud Computing, Data Science & Engineering (Confluence)*, January 29-31, 2020, pp. 480-484. https://doi.org/10.1109/Confluence47617.2020.9057889.

[2] P. P. Patel, and D. B. Vaghela, "Crop diseases and pests detection using convolutional neural network," *Proceedings of the 2019 IEEE International Conference on Electrical, Computer and Communication Technologies (ICECCT)*, February 20, 2019, pp. 1-4. https://doi.org/10.1109/ICECCT.2019.8869510.

[3] K. Singh, S. Kumar, and P. Kaur, "Automatic detection of rust disease of Lentil by machine learning system using microscopic images," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 9, no. 1, p. 660, 2019, https://doi.org/10.11591/ijece.v9i1.pp660-666.

[4] E. Hirani, V. Magotra, J. Jain, and P. Bide, "Plant disease detection using deep learning," *Proceedings of the 2021 6th International Conference for Convergence in Technology (I2CT)*, April 2, 2021, pp. 1-4. https://doi.org/10.1109/I2CT51068.2021.9417910.

[5] O. Kulkarni, "Crop disease detection using deep learning," *Proceedings of the 2018 Fourth International Conference on Computing Communication Control and Automation (ICCUBEA)*, August 16, 2018, pp. 1-4. https://doi.org/10.1109/ICCUBEA.2018.8697390.

[6] P. Tm, A. Pranathi, K. Sai Ashritha, N. B. Chittaragi, and S. G. Koolagudi, "Tomato leaf disease detection using convolutional neural networks," *Proceedings of the 2018 Eleventh International Conference on Contemporary Computing (IC3)*, August 2, 2018, pp. 1-5, https://doi.org/10.1109/IC3.2018.8530532.

[7] H. Ajra, M. K. Nahar, L. Sarkar, and Md S. Islam, "Disease detection of plant leaf using image processing and CNN with preventive measures," *Proceedings of the 2020 Emerging Technology in Computing, Communication and Electronics (ETCCE)*, December 21, 2020, pp. 1-6. https://doi.org/10.1109/ETCCE51779.2020.9350890.

[8] C. R. Rahman *et al.*, "Identification and recognition of rice diseases and pests using convolutional neural networks," *Biosyst Eng*, vol. 194, pp. 112–120, 2020, https://doi.org/10.1016/j.biosystemseng.2020.03.020.

[9] D. Tiwari, M. Ashish, N. Gangwar, A. Sharma, S. Patel, and S. Bhardwaj, "Potato leaf diseases detection using deep learning," *Proceedings of the International Conference on Intelligent Computing and Control Systems, ICICCS 2020*, May 2020, pp. 461–466. https://doi.org/10.1109/ICICCS48265.2020.9121067.

[10] G. Zhou, W. Zhang, A. Chen, M. He, and X. Ma, "Rapid detection of rice disease based on FCM-KM and faster R-CNN fusion," *IEEE Access*, vol. 7, pp. 143190–143206, September 24, 2019, https://doi.org/10.1109/ACCESS.2019.2943454.

[11] G. R. Beecher, "Nutrient content of tomatoes and tomato products," *Proceedings of the Society for Experimental Biology and Medicine*, vol. 218, no. 2, pp. 98–100, 1998. https://doi.org/10.3181/00379727-218-44282a.

[12] M. Sardogan, A. Tuncer, and Y. Ozen, "Plant leaf disease detection and classification based on CNN with LVQ algorithm," *Proceedings of the 2018 3rd International Conference on Computer Science and Engineering (UBMK)*, September 20, 2018, pp. 382-385. https://doi.org/10.1109/UBMK.2018.8566635.

[13] Md H. Ahmed, T. Islam, and R. Rahman Ema, "A new hybrid intelligent GAACO algorithm for automatic image segmentation and plant leaf or fruit diseases identification using TSVM classifier," *Proceedings of the 2019 International Conference on Electrical, Computer and Communication Engineering (ECCE)*, February 7, 2019, pp. 1-6, https://doi.org/10.1109/ECACE.2019.8679219.

[14] S. M. Hassan, A. K. Maji, M. Jasiński, Z. Leonowicz, and E. Jasińska, "Identification of plant-leaf diseases using CNN and transfer-learning approach," *Electronics (Switzerland)*, vol. 10, no. 12, p. 1388, 2021, https://doi.org/10.3390/electronics10121388.

[15] "PlantifyDr Dataset | Kaggle," [Online]. Available at: https://www.kaggle.com/datasets/lavaman151/plantifydr-dataset.

[16] J. Liu and X. Wang, "Tomato diseases and pests detection based on improved Yolo V3 convolutional neural network," *Front Plant Sci*, vol. 11, p. 898, 2020, https://doi.org/10.3389/fpls.2020.00898.

[17] M.-L. Huang and T. C. Chuang, "A database of eight common tomato pest images," Mendeley Data, vol. 1, 2020.

[18] A. Gondal, M. Ijaz, K. Riaz, and A. Khan, "Effect of different doses of fungicide (Mancozeb) against alternaria leaf blight of tomato in tunnel," *J Plant Pathol Microbiol*, vol. 3, no. 3, p. 2, 2012, https://doi.org/10.4172/2157-7471.1000125.

[19] P. Kaur *et al.*, "Recognition of leaf disease using hybrid convolutional neural network by applying feature reduction," *Sensors*, vol. 22, no. 2, p. 575, January 22, 2022, https://doi.org/10.3390/s22020575.

[20] V. Agarwal, "Complete architectural details of all EfficientNet models towards data science," [Online]. Available at: https://towardsdatascience.com/complete-architectural-details-of-all-efficientnet-models-5fd5b736142.

[21] Z. P. Jiang, Y. Y. Liu, Z. E. Shao, and K. W. Huang, "An improved VGG16 model for pneumonia image classification," *Applied Sciences (Switzerland)*, vol. 11, no. 23, p. 11185, 2021, https://doi.org/10.3390/app112311185.

[22] "ML: Getting started with AlexNet – GeeksforGeeks," [Online]. Available at: https://www.geeksforgeeks.org/ml-getting-started-with-alexnet/.

[23] "Everything you need to know about VGG16 medium," [Online]. Available at: https://medium.com/@mygreatlearning/everything-you-need-to-know-about-vgg16-7315defb5918.

[24] I. Z. Mukti, and D. Biswas, "Transfer learning based plant diseases detection using ResNet50," *Proceedings of the 2019 4th International Conference on Electrical Information and Communication Technology (EICT)*, December 20, 2019, pp. 1-6. https://doi.org/10.1109/EICT48899.2019.9068805.

[25] A. Rastogi, "ResNet50. ResNet-50 is a convolutional neural," [Online]. Available at: https://blog.devgenius.io/resnet50-6b42934db431.

***PROTHAMA SARDAR** is a student of Computer Science and Engineering at Jashore University of Science and Technology.*

She is now a student at the graduate level. She is very interested in the machine learning, deep learning-based thesis. Machine learning is one of the trending research topics nowadays.

Sardar contributes to the research of the deep learning approach. That is very interesting work for her.

***ROMANA RAHMAN EMA** is currently working as an Assistant Professor in the department of Computer Science and Engineering at Jashore University of Science and Technology (JUST), Bangladesh. On 2020, she joined at Jashore University of Science and Technology as a Lecturer. Before joining at JUST, she was working as a Senior Lecturer in the department of Computer Science and Engineering at North Western University, Khulna, Bangladesh. Romana Rahman Ema received B.Sc. (Engg.) and M.Sc. (Engg.) in Computer Science and Engineering (CSE) from Jashore University of Science and Technology (JUST), Bangladesh in 2013 and 2015 respectively.*

***SK. SHALAUDDIN KABIR** is a lecturer of Computer Science and Engineering at Jashore University of Science and Technology.*

He, before joining at JUST, was working as a Lecturer in the department of Computer Science and Engineering (CSE) at Northern University of Business and Technology Khulna (NUBTK), Khulna, Bangladesh. He also worked as an Instructor in the department of Computer at Model Polytechnic Institute, Jashore.

***DR. MD. NASIM ADNAN** is an assistant professor of Computer Science and Engineering at Jashore University of Science and Technology.*

He received BSc in Computer Science and Engineering (CSE) from Khulna University, MSc in CSE from Bangladesh University of Engineering and Technology (BUET) and PhD from Charles Sturt University (Australia) in 2002, 2010 and 2017 respectively. Previously he worked as an Assistant Professor in University of Liberal Arts Bangladesh (ULAB).

***DR. SYED MD. GALIB** is a professor of Computer Science and Engineering at Jashore University of Science and Technology.*

He finished his PhD from Swinburne University of Technology, Australia in 2015. Before that, he completed his Master of Science in Computer Engineering (specialization in Artificial Intelligence) from Dalarna University, Sweden in 2008. He obtained his Bachelor Science in Computer Science and Engineering from Khulna University, Bangladesh in 2005.

Dr. Galib, currently, is the chairman of the department of CSE, JUST. Moreover, he leads a research group named Artificial Intelligence for Development (AID group) within the department of CSE. His research interest is mostly in the field of Image Processing and Artificial Intelligence applied to social development.