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Deep Learning Technology based Night-CNN for Nightshade Crop Leaf Disease Detection

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Abstract: crop diseases pose a serious death trap to food safety, but their rapid disease diagnosis remains burdensome in many parts of the world due to the lack of the necessary foundation. These days, deep learning models have shown better performance than hi-tech machine learning techniques in several fields, with computer vision being one of the most noticeable cases. Agronomy is one of the domains in which deep learning concepts have been used for disease identification on different parts of plants. Having a disease is very normal and common, but prompt disease recognition and early avoidance of crop diseases are crucial for refining production. Although the standard convolutional neural network models identify the disease very accurately but require a higher computation cost and a large number of parameters. This requires a model to be developed which should be efficient and need to generate less no of parameters. This research work proposed a model to identify the diseases of plant leaves with greater accuracy and efficiency compared to the existing approaches. The standard models like AlexNet, VGG, and GoogleNet along with the proposed model were trained on the Night shed plants leaf which is available in the plant village. It has 9 categorical classes of diseases and healthy plant leaves. A range of parameters, including batch size, dropout, learning rate, and activation function were used to evaluate the models' performance or achievement. The proposed model achieved a disease classification accuracy rate of 93% to 95%. According to the findings of the accuracy tests, the suggested model is promising and may have a significant influence on the speed and accuracy with which disease-infected leaves are identified.

Keywords: Deep learning, Night shed crops leaf diseases, Hyperparameters, Night-CNN (Proposed model), Treatments

1. Introduction

Crop disease identification is an art and science. The disease identification technique is integrally visual and requires intuitive judgment and the use of scientific approaches. Approximately 75% of India's population relies on farming, which is a major source of income for the nation. Disease on crops leads to a significant reduction in both the quality and quantity of agricultural products. In agriculture, plant diseases happen because of changes in climate like more or less rainfall, very hot or cold temperatures, and weather cycles from one place to another. Climate change may affect the crops by bacterial infections, fungal, as well as viruses which damage the crop, develop disease, and gradually collapse the crop quality. Crop diseases can affect the entire crop by interfering with different manners like translocation as well as absorbance of nutrients and water, photosynthesis, fruit and flower development, plant development and growth, and enlargement and cell division. Plant diseases may damage the plant above and below the ground level as well. Diseases may develop in different parts of the plant body.

Crop disease control is a challenging task for farmers. Preventive actions may be taken early on reducing both economic and production losses, if these illnesses are detected in their early stages [Islam Dinh, Wahid, Bhowmik, 2017]. For the purposes of plant disease research, visual patterns on the crop are considered the primary data source. Controlling and preventing the spread of disease across the whole farm is essential to ensuring the greatest possible yield and quality. Classifying a disease based on symptoms, determining its root cause, and then attempting to manage it is essential to stop its spread.

Crop disease monitoring and analysis were traditionally done manually by specialists in the field. Manually identifying the disease requires extensive work and it consumes more time. The innovation in deep learning techniques like convolution neural networks may be used in plant disease identification which requires some resources but it identifies the correct disease automatically.

In accordance with that, the research aims to:

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- Introduced the Convolution Neural Network based Night-CNN model which is not expensive, so normal farmers can use this model for detection of night shed crop diseases.
- The proposed Night-CNN model also suggested remedial measures in the field of agriculture for plant diseases which happen due to fungal, bacterial, and viruses.
- The proposed Night-CNN model generates the accurate result for disease identification in less amount of time.
- Training required less number of resources and time for the disease of the night shed crop.

This research work is mainly concentrated on a very essential part of the plant, the leaf. Leaf disease detection may be based on the symptoms including brown dots, spotting, yellow dots, etc. which have been caused due to bacterial, fungal, and viral infections. In most cases, farmers detect the disease with their naked eye [Arivazhagan, 2013], but such a process is fairly taking too much time and is inappropriate in the farming area. Farmers may require the assistance of professionals in determining the disease's identity sometimes. It is easier to classify diseases because of the availability of automated methods that decrease the need for effective manpower and the expense of farmers. There is a great amount of complexity in the automated algorithms used to categorize plant leaf diseases using optical monitoring of signs on plant leaves [Ferentinos, 2018]. Diagnosis of the disease in the plant leaves and at the same time delivering a healthier solution to control it, will be obliged to farmers to produce a good quality and quantity of the crop. Leaf makes food and the different part of the plant use that food for their growth. The disease control on a leaf is the major task in agriculture. There is no such common model exists which identifies the disease which happens due to fungus, bacterial, and viruses. The Night-CNN is identifying all types of diseases which happen due to viruses, fungi, and bacteria in the Lycopersicon crop.

Plant leaf sicknesses appear due to environmental and climate changes. Having a disease in the crop is a herbal issue. The ailment can appear within the crop for a unique reason. Fungi, microorganisms, phytoplasma, viruses, viroid, nematodes, and many others. [Joshi and Bhavsar,2020] are examples of the sickness. diseases like Canker, Aster yellow, fireplace blight, Rice bacterial blight, Bacterial wilt, Crown gall, Rot, Basal rot, Scab are examples of bacterial sickness. The fungal diseases are a late blight, Anthracnose, Blight, Chestnut blight, Canker, Clubroot, Damping off, Black knot, Dutchelm disease, Ergot, Fusarium wilt, Panama disease, Leaf blister mold, Powdery mildew, Downy mould, o.k.wilt, Rot, Basal rot, grey mould rot, Rust. Mosaic, Curly pinnacle, Psoriasis, noticed wilt, and so forth. are manifest because of the virus.

Agriculture-related research has been extensive in identifying diseases in many plants and crop parts, including roots, fruit, leaves, soil, and weeds, for instance. Smartphones, internet penetration, and unmanned aerial vehicle technologies offer new tools for in-field plant disease detection based on automated image recognition that can aid in early detection at a large scale [Ramcharan, Baranowski, McCloskey, Ahemed, Legg and Hughes, 2017]. Once a disease is diagnosed, the reason for the disease should be investigated, and after that certain preventive actions are to be applied to stop the spread of the disease in the future [Rathod, Tanawal, Shah,2013]. Crops can have distinct causes and symptoms of the disease. This research work concentrated on the detailed study of diseases of Lycopersicon crops and the timely detection of such diseases using deep learning algorithms. Table1 describes the different diseases with their scientific names on Night shed crops [Sankaran, Mishraa, Ehsania, Davisb, 2010] [Moda, Jadhav, Naikwadi,2014].

Table:1 Lycopersicon, Tuberosum, Capsicum annuum Leaf Diseases [JOSHI AND BHAVSAR,2020]

Bacterial Disease	
Common Name	**Scientific Name**
Bacterial Spot	Xanthomonas Vesicatoria
Fungal Disease	
Early Blight	Alternaria Solani
Late Blight	Phytophthora Infestans
Leaf Mold	Fulvia Fulva
Septorial Leaf Spot	Lycopersicon
Target Spot	Corynespora cassiicola
Viral Disease	
Mosiac Virus	Lycopersicon virus 1
Yellow Leaf Curl Virus	Solanum Lycopersicon
Two Spotted Spider mites	Tetranychrus Urticae

The inception CNN was utilized by Amanda Ramcharan et al. to classify the infection in cassava leaves. The image processing was utilized to extract features, and then the CNN was used to identify diseases. For cassava leaf disease, this method is 93% to 98% accurate. The authors have identified the diseases based on fungi. The Night-CNN only works for the fungal disease of cassava leaves. They have also created a smartphone app that can identify diseases quickly [Ramcharan, Baranowski, McCloskey, Ahmed, Legg, and Hughes,2017]. There are a variety of CNN architectures for crop disease detection and diagnosis, including AlexNetOWTBn, AlexNet, Overfeat, VGG, as well as GoogLeNet [Ferentinos,2018]. VGG has the greatest success rate and the best fit between laboratory data and actual data among all these models. The morphological idea has also been employed by the authors to identify plant diseases. The Night-CNN only identifies the bacterial leaf disease of various leaf-like banana, apples, cabbage, onion, orange, tomato, and potatoes. Classification of Leaf Diseases in Plants, CNN and LVQ Algorithm was used to identify plant diseases using the "Learning Vector Quantization" approach for feature extraction [Ozen, Tuncer, Sardogan, 2018]. Diseases including late blight, bacterial spots, yellow-curved leaf disease on tomato crops as well as septoria leaf spots were discovered using this method. The algorithm is 86% given an accurate result. Sometimes it identifies the wrong disease.

Artificial Neural Network (ANN) and grey level co-occurrence matrix (GLCM) were used to classify pomegranate plant disease [Dhakate, 2020]. [Bharti,2011]. Diseases such as fruit spots, fruit rot, bacterial blight, and leaf spot are identified by these algorithms. The algorithm was only applied to the laboratory dataset for bacterial disease identification.The masking technique was utilized by Monzurul Islam et al. to extract features and train an SVM for disease detection [Islam Dinh, Wahid, Bhowmik, 2017]. SVM was formerly used to detect infections in potato plants, such as early blight and late blight. The model only works for the potato leaf in the bacterial disease identification process. The model identified the disease, that is, in the small dataset.The detection of infection on beans, rose, banana, lemon, tomato, mango, and jackfruit crops is shown by the classification of sick areas of plant leaves utilizing Genetic Algorithms as well as Image Processing [Singh, Varsha, Misra,2015]. The classification as well as feature extraction techniques uses a genetic algorithm. The algorithm only works for the synthetic dataset.

Features extracted from pepper plants via masking grey pixels and threshold-based segmentation were employed by Jobin Francis et al. for classification using a neural network [Francis Sahaya, Anoop, 2016][Camargoa, Smith, 2009]. Authors discovered problems including rapid wilt and berry spots. In addition, researchers have discovered the cause of the infection and taken Preventive measures to stop it from spreading. An anomaly detection and plant leaf disease detection of the tomato crop is provided by Robert G. de Luna et al. [Luna, Dadios, Bandala, 2018]. Fully-Region CNNs are used to identify plant anomalies, whereas CNNs are utilized to identify diseases. After determining the disease's categorization, they recommended a particular treatment. This prototype may be used for any Lycopersicon crop since it automatically captures pictures via the box. Leaf Miners, Target Spots, as well as Phoma Rot may all be accurately detected with this technique. The algorithm works for the fungal disease of the pepper plant leaf.In [Prakash, Saraswathy, ramalakshmi,2017], Plant leaf disease detection was suggested utilizing image classification and processing by the authors. Uses GLCM ("Gray Level Co-officiant method") and k-means clustering for feature extraction, and an SVM to classify images. In the case of citrus leaves, this algorithm is utilized. The algorithm only works for the specific angle of the laboratory dataset. The algorithm works for the disease happens in the crop leaf or not without specifying the actual disease name.

Srdjan Sladojevic et al. introduced the convolution neural network for the disease identification model. The initial step in this approach is to gather all photographs and delete those that are duplicates [Sladojevic,2016]. The images are carefully resized using the preprocessing procedure. For example, the augmentation technique may be used to increase the data size and add a little distortion to the pictures. For the augmentation procedure, the Python OpenCV package is utilized. To detect diseases including grapevine wilt, apple powdery mildew, peach powdery mildew, and CaffeNet framework was utilized for the CNN classification [25]. Reasonable outcomes may have been achieved using augmentation processes. The algorithm gives a good result for the synthesis dataset.

In [Liakos, Busato, Moshou, Pearson, Bochtis,2017] discuss the unique application of mastering systems based on agricultural production. Researchers have explored the fields of crop control, which include programs on yield prediction, disease detection, weed detection, crop fines, and species recognition, farm animals control, which includes packages on animal welfare and livestock manufacturing, water control, and soil control management. Articles are organized according to category and filtered according to filtering, which indicates how machine mastering can benefit agriculture. In the era of machine learning and sensor data, farm management systems are becoming AI-enabled, real-time programs that support and guide farmer decision-making.

The authors [Pantazi, Tamouridou, Alexandrite Lagopodi, Kontouris Moshou,2017] of this study presented a technique that led to a description of the chemistry of S. marianum flora by using subject spectroscopic evaluations and hierarchical self-organizing maps. There are three supervised hierarchical self-organizing concepts or models used for the identification of systemically inflamed S. marianum flowers: the Kohonen community, the counter propagation synthetic neural network, and the XY-Fusion community. Pre-processing of the spectra protected normalization, 2nd spinoff, and primary element extraction. Identification of S. marianum with SKN and CP-ANN offered high overall accuracy and even performed better than XY-F. Through hierarchical self-organizing maps, it was possible to identify systemically inflamed S.marianum flowers with an excessive degree of accuracy throughout vegetative growth.

The main objective of the [Ebrahimi, Khoshtaghaza, Minaei, Jamshidi,2017] observation is to locate thrips on the crop cover photos using the SVM approach. For sorting parasites and detecting thrips, SVM with different kernel characteristics is utilized. It uses the ratio of big diameter to a small diameter as a location index along with hue, saturation, and intensity as color indices. Additionally, we suggest square mistakes, the root of suggested square errors, suggest absolute errors, and implied percent error were used for evaluating the classification. With the use of the SVM approach, its results demonstrated that an average percentage error of less than 2.25% is achieved in the high-quality category when the area index and intensity are used as color indexes.

At 3 weeks of age, seedlings afflicted with Bakanae disease [Chung Huang, Chen, Lai, Chen, Kuo, 2016], may be distinguished from healthy seedlings using a machine vision technique. Healthy as well as infected seedlings could be differentiated with an accuracy of 87 percent using the suggested method.

Table:2 Literature review summary

Author	**Result Accuracy**	**Used Algorithm**
Amanda Ramcharan et al. [4] - 2017	93% to 98%	CNN, SVM, KNN
Konstantinos P. Ferentinos et al.[3] - 2018	99.53%	CNN applied on the VGG, AlexNet, and GoogleNet Architecture
Melike Sardogan et al. [5] - 2018	86%	CNN, LVQ
Murunmayee Dhakate et al. [6]-2015	90%	Image Processing K-means, GLCM and Neural Network
Monzurul Islam et al. [2] - 2017	95%	Image Processing and machine learning
Vijay Singh et al. [7]-2015	-	Image processing and classification
Jobin Francis et al. [8]-2016	-	Image segmentation and Neural Network
Robert G. de Luna et al. [18] - 2018	-	CNN
R. Meena Prakash et al.. [19]- 2017	-	Image processing and Classification
Liakos KG et al. [27] - 2018		Machine Learning algorithms, models, statistic measures,
Pantazi, X.E. et al. [28] - 2017	95.16%	ANN /XY Fusion
Sk Mahmudul Hassan et al. [31]-2021		CNN and Transfer learning
Barkha M. Joshi & Bhavsar [26] - 2020		AlexNet, VGG and GoogleNet
Barkha M. Joshi & Bhavsar [46]- 2022	93% to 95%	Disease identified for Lycopersicon crop leaf of plain background

An overview of plant leaf disease identification research is provided through a literature review. Table 2 covers the used algorithms in the different disease identification processes. Even though a great deal of study has been done in this field, there are still certain limits that must be overcome like developed models may require a lot of resources. AlexNet, VGG, and GoogleNet have generated very much high parameters, so all those models required more time for training, the developed models only work on a single dataset and identify the limited no of the disease means fungal, bacterial, or viral, no such models available which identifies all types of disease on synthetic data and real data. This research work proposed a Night-CNN model which solved the problem of resources. The Night-CNN efficiently detects different types of fungal, bacterial, and viral diseases on Lycopersicon, Tuberosum, Capsicum annuum using deep learning concepts.

The organization of this article is as follows: Section 2 describes the material and methods. Implementation and results are described in Section 3. Conclusion and future work are explained in Sections 5 and 6, correspondingly.

2. Material And Methods

Interest in Convolution Neural Networks has currently heaved, and deep gaining knowledge of the most famous approach wherein exclusive styles of structure fashion can research suitable capabilities from input photographs at one-of-a-kind convolutional levels comparable, to the features of the human mind. This version of DL includes convolution, pooling layers, and fully linked layers as well as activation capabilities to deal with composite issues correctly and quickly with high accuracy.

The Proposed Night-CNN model has been implemented in Python language. The model is implemented in the TensorFlow environment. Keras is one of the best libraries for the convolution network, which is installed on the TensorFlow environment. There are many libraries like pandas, NumPy, OpenCV, matplotlib, scikit used to implement the convolution-based Night-CNN. The Night-CNN uses 11x11,3x3 and 1x1 filters on the convolution layer for feature extraction. Each convolution layer is followed by the max pool layer, which is used to reduce the dimension of the images.
As shown in Table 3, different CNN architectures such as AlexNet, VGG, and GoogleNet have various layers and parameter sizes.

Table:3 Comparison of Night-CNN with Other model parameters and filters

Invented Year	**Name of Architecture**	**Total No of Layers**	**Parameters**	**Filters**	**Limitation**
2012	AlexNet	8	60M	11x11, 5x5 and 3x3	1. Hard to apply the high-Resolution Image 2. Overfitting Problem
2014	VGG	16	134M	3x3 and 2x2	1. It takes more time to train the model. 2. It takes a lot of disk space and bandwidth making it inefficient. 3. Vanishing Gradient Problem. 4. More Complex than AlexNet. 5. Expensive
2014	GoogLeNet	22	360M	1x1, 3x3, 5x5	1. Required more computing power to train the model. 2. Overfitting Problem 3. More time required for training 4. Expensive
2022	Night-CNN (Proposed Model)	6	26M	11x11, 3x3, and 1x1	1.Identify the night shade crop disease accurately

The standard model uses a different type of filter. The basic architecture diagrams of the CNN model like AlexNet, VGG, and GoogleNet are demonstrated in figure1. The standard architecture model used convolution layer, max-pooling layers, and fully connected layer for disease identification. The model used the different no layers for the disease identification. The standard model generates very large parameters due to that reason, it takes more time to execution, and it requires a large no of the resource.

Hence Night-CNN used less no of layers and generates fewer parameters so that the computation time and resource cost will be reduced. In this research work, we we compared the result with the standard model.

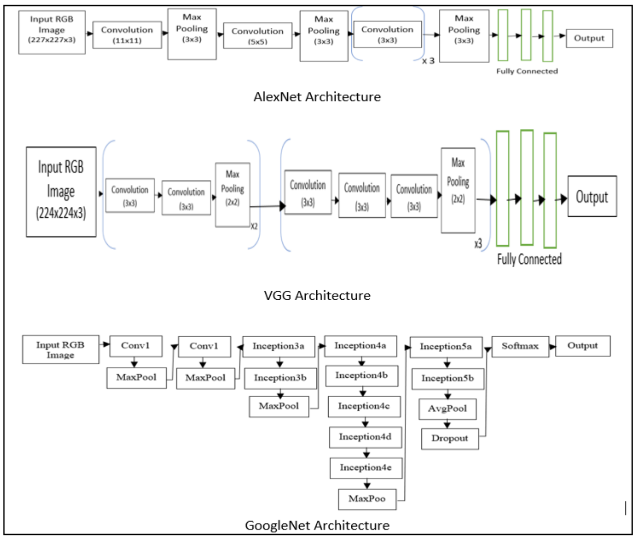

Fig:1 CNN model Architecture

3. Proposed Work

Although AlexNet, VGG, and GoogleNet architectures are powerful and accurately identify disease, this architecture requires very large resources and computation time to identify the disease. Hence, disease identification using deep learning requires such a model which identifies the disease very accurately in less amount of time with a limited no of resources. The suggested model utilizes the max-pooling layer, convolution layer, activation function, as well as a fully connected layer for the classification of the specific disease. The Night-CNN uses five convolution layers with single fully connected layer.

Dataset: An open-access Plant Village dataset of 50,000 infected and healthy plant leaves [2] was utilized for testing and training purposes. All photos in the database were taken in laboratory conditions from 14 distinct species of plants. We used Lycopersicon, Tuberosum and Capsicum annuum crops with healthy and unhealthy leaves in our experiment. The dataset size of Lycopersicon is 20304. In figure 2, shows color images of Lycopersicon, Tuberosum and Capsicum Annuum crop leaves. The disease names, no images, are displayed in Table 4. The experiment used the RGB color images for disease identification.

Table:4 Lycopersicon[46], Tuberosum and Capsicum Annuum crop leaf disease images dataset

Crop Name	Class No	No of Images	Class Name
Lycopersicon	1	1404	Target Spot
	2	373	Mosaic Virus
	3	3209	Yellow Leaf Curl Virus
	4	2127	Bacterial Spot
	5	1000	Early Blight
	6	1591	Healthy
	7	1909	Late Blight
	8	952	Leaf Mold
	9	1771	Septoria Leaf Spot
	10	1676	Two Spotted Spider Mite
Tuberosum	1	927	Early Blight
	2	127	Healthy
	3	919	Late Blight
Capsicum annuum	1	917	Bacterial Spot
	2	1402	Healthy

All diseased classes are imbalanced, we have used the augmentation process to make the no of image size balanced in all types of disease. A total of two sets of leaf images were used, a testing and training set. For evaluation, leaf images were split into 80% training images and 20% testing images.

Pre-processing: There are five approaches applied on the dataset for the experiment of disease diagnosis. The augmentation technique is used for a horizontal and vertical shift, flip, random rotation, brightness, and zoom of the images. Different types of methods make the dataset balanced for the disease identification process. There are so many irrelevant images in dataset, so data cleaning technique is used to remove the noise from the image dataset. The images are in different sizes and shapes so that editing is required. All images are converted in to 227x227x3 images. The leaf disease detection image reduction technique is used to extract the features very accurately. All these techniques are used as a preprocessing for the proposed algorithm.

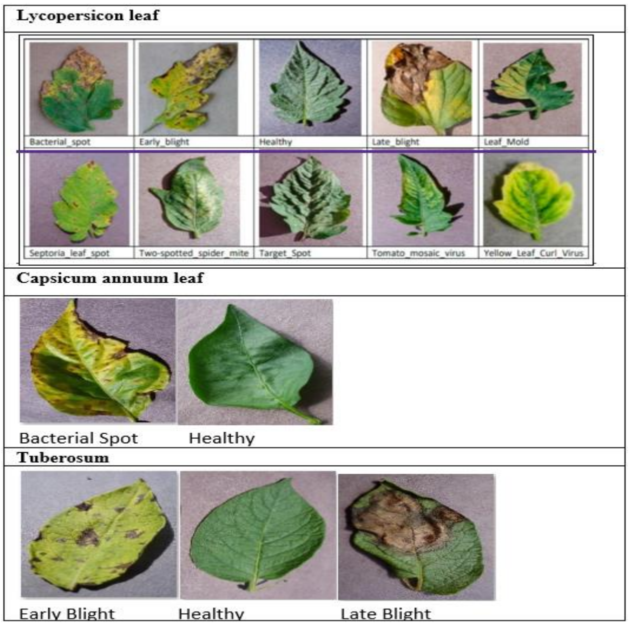

Fig:2 Lycopersicon, Capsicum annuum Tuberosum crop leaf classification

Proposed-Night CNN Architecture: Night-CNN uses 227x227x3 RGB images as an input. All images are passed through different layers. The Night-CNN contains the 5-convolution layers. All layers are followed by the max-pooling layers. A single fully connected layer is used for the classification of the disease. We have used 11x11, 3x3, and 1x1 filters on different layers for the feature selection. Figure:3 depicts the Night-CNN architecture.

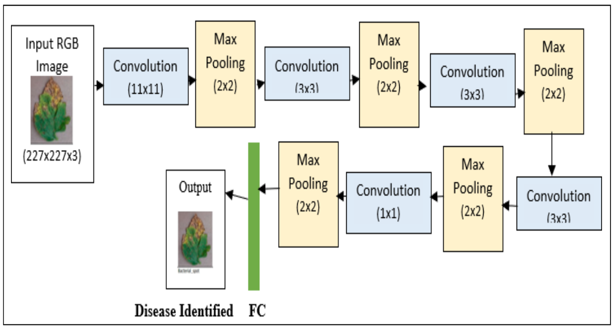

Fig:3 Proposed Night-CNN architecture

Convolution layer: Width, Height, and Depth are all learnable filters in a convolutional algorithm. An image matrix is used to represent the input picture and the filter slides through it to produce a filtered image, which is the result of the filtering process. In the case that a filter is applied to a picture, the output matrix will be smaller than the original. The output matrix would be smaller than the original picture if a filter were applied to the input one. To ensure that the output size matches the input size, padding is required. Convolution is used to extract features from a dataset. In the proposed Night-CNN, 2D convolutions are useful when building convolutional neural networks or for standard image processing filters like blurring, sharpening, and edge identification. They are built on the principle of iterating through an input image to create an output image using a kernel. Input data will be transformed linearly by convolution based on the spatial information in the data. Convolution kernels may be trained based on CNN input by adjusting the weight of that layer's weight.

Activation function: The activation function of the ReLU has been enhanced with the inclusion of the Leaky ReLU. For the ReLU activation function, the gradient is 0 for all input values that are less than zero, which would deactivate the neurons in that area and may lead to the death of ReLU neurons. To deal with this issue, the term "leaky ReLU" is used. A small linear component is defined as a negative value of the ReLU activation function, rather than zero for negative inputs (x).

$$f(x) = \max(0.01*x, x)$$

Pooling Layer: The pooling layers have been utilized to gradually decrease the image size. The pooling layer resizes the input by applying the pooling function to each layer of the input. The max-pooling layer has been used in the proposed Night-CNN. Every depth slice in the input is downsampled by two along with both height and width in pooling layer 2×2 size, resulting in a loss of 75% of the activation.

Fully connected layer: The final layer is called the fully connected layer. This layer is used for the dimensionality reduction process. These two-dimensional arrays are transformed into a single long linear vector by this layer. This Night-CNN uses a single fully connected layer, which generates less no of parameters.

Output: Diseases are classified as healthy or unhealthy with specific diseases.

4. Implementation And Results

In the Night-CNN, we have used the single fully connected layer which generates the least no of parameters over the AlexNet, VGG, and GoogLeNet architectures. Table 5 describes the hyperparameters are considered for the Night-CNN.

Hyperparameter	Description
No. of convolution layer	5
No. Fully connected layer	1
Dropout rate	0.5
Activation function	LeakyRelu
Learning rate	0.0001
Number of epochs	500
Batch size	32

Table:5 Hyperparameters of Night-CNN

$$\left(\text{Shape of width of filter} * \text{Shape of height of filter} * \text{Previous layer filter or feature map} + 1 \right) * \text{No of Filter for current Layer}$$

The no of the parameters may be computed with [{(Shape of a width of filter * the shape of the height of filter * previous layer filter or feature map) + 1} * No of the filter for the current layer] formula. Parameter comparison of the Night-CNN (proposed model) over AlexNet, VGG, and GoogleNet is depicted in figure 4. The Night-CNN generates less no of parameters due to a single fully connected layer. Class wise predictions of Lycopersicon leaf diseases and Tuberosum and Capsicum annuum leaf diseases are displayed in figure 5 and figure 7 respectively. Figure 6 and figure 8 displayed the accuracy in terms of precision, recall, and f1-score of Lycopersicon, Tuberosum and Capsicum annuum.

AlexNet, VGG, GoogleNet, and Proposed models have been executed in a google cloud environment with Tesla T4 GPU. The proposed model is implemented in Python language. The code implementation we have used the Google cloud services. We have used the standard tomato image data set for the training purpose. Training purpose, we have considered 80% training data and 20% testing dataset. The layered wise implemented structure is depicted in Figure 9. The model's wise accuracy comparison is depicted in Figure 10 and Figure 16.. The results demonstrated that the Night-CNN gives more accuracy than the other three models. The Night-CNN gives 93% to 95% training and testing accuracy. The Night-CNN generates the least number of parameters so that it requires less amount of time to identify the disease accurately. Figure 11 describes the chart for the training testing accuracy. As the results show that the training and testing accuracy increases when the epochs increase. Accuracy increases until the threshold value is 500 epochs.

We must get good training and testing accuracy, but at the same time, we have to consider the loss. Figure 12 depicts the comparison of the error rate over the AlexNet, VGG, and GoogleNet. of the Night-CNN over the other three models. Results proved that the loss is less over the other standard model.

Figure 13 displays the training and testing loss of the Night-CNN. The model has been executed on the Google cloud environment with the Tesla T4 GPU. The research work has been carried out on the plain background plant leaf images Convolution neural networks used some hyperparameters to train the model accurately without overfitting and underfitting problems.

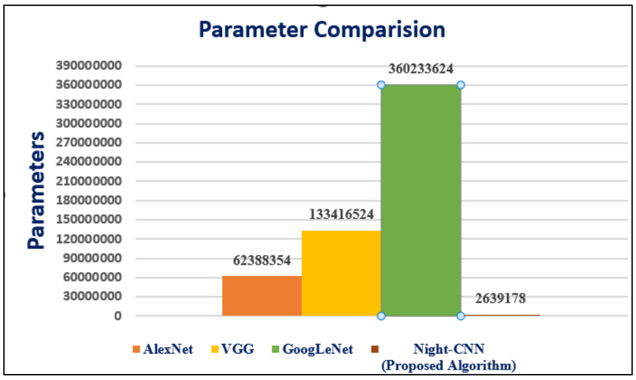

Fig:4 Night-CNN Parameter comparison

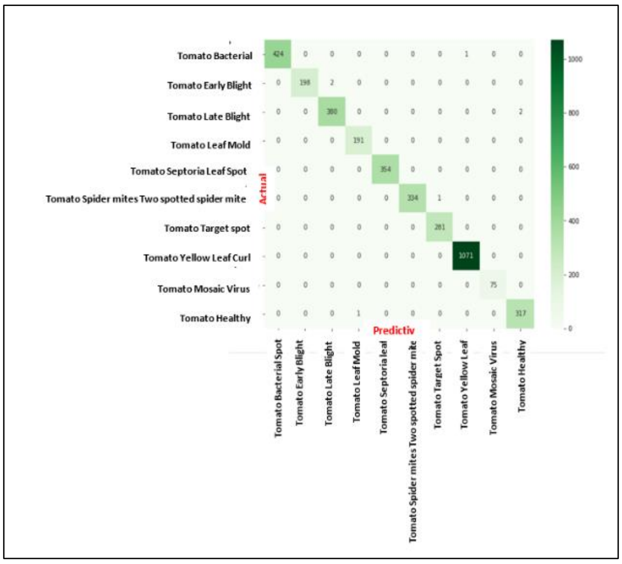

Fig:5 Confusion Matrix of Lycopersicon crop Diseases [46]

	precision	recall	f1-score	support
0	1.00	1.00	1.00	425
1	0.95	1.00	1.00	200
2	1.00	0.93	1.00	382
3	0.94	0.94	0.95	191
4	1.00	1.00	1.00	354
5	0.94	0.95	1.00	335
6	1.00	1.00	0.94	281
7	1.00	1.00	1.00	1071
8	1.00	1.00	0.95	75
9	0.95	1.00	1.00	318
accuracy			95.23	3632
macro avg	0.94	0.94	0.94	3632
weighted avg	0.94	0.94	0.93	3632

Fig:6 Accuracy Matric of Lycopersicon [46]

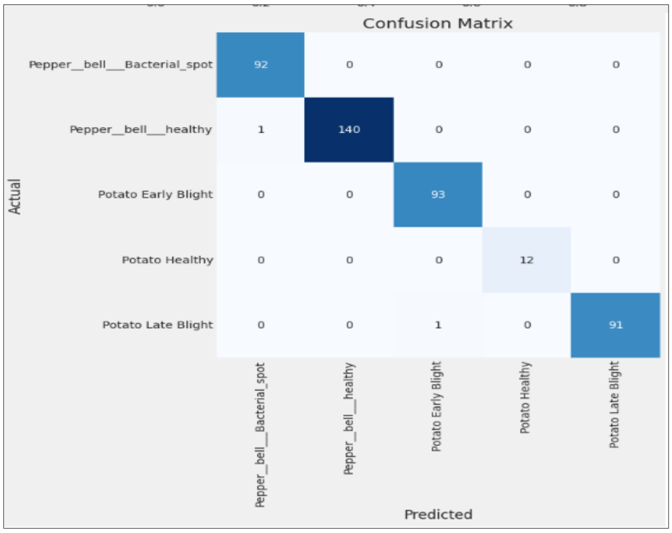

Fig:7 Confusion Matrix of Tuberosum and Capsicum Annuum

Classification Report:
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	precision	recall	f1-score	support
Pepper__bell__Bacterial_spot	0.99	1.00	0.99	92
Pepper__bell__healthy	1.00	0.99	1.00	141
Potato Early Blight	0.99	1.00	0.99	93
Potato Healthy	1.00	1.00	1.00	12
Potato Late Blight	1.00	0.99	0.99	92
accuracy			1.00	430
macro avg	1.00	1.00	1.00	430
weighted avg	1.00	1.00	1.00	430

Fig:8 Accuracy Matric of Tuberosum and Capsicum Annuum

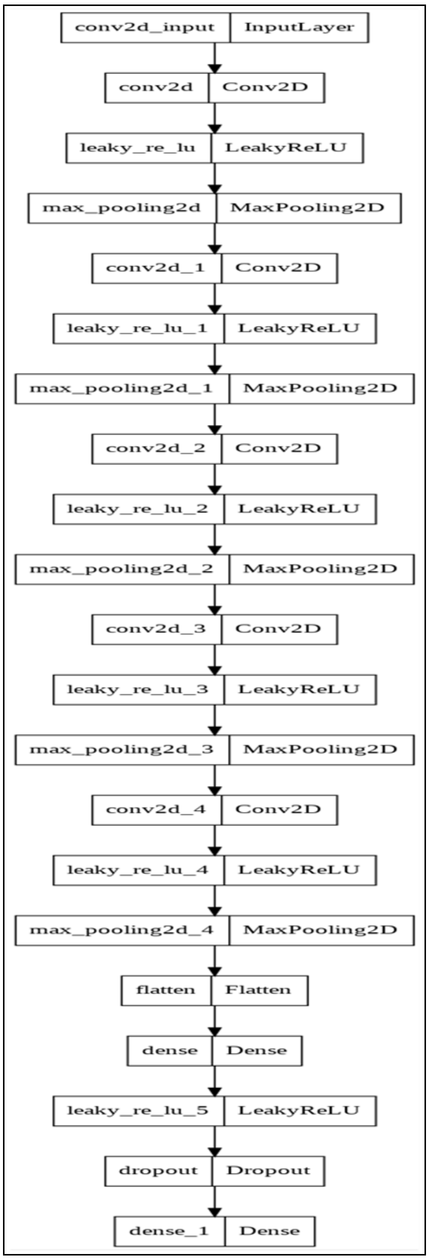

Fig:9 Parameters based implemented Proposed Night-CNN Layered Structure

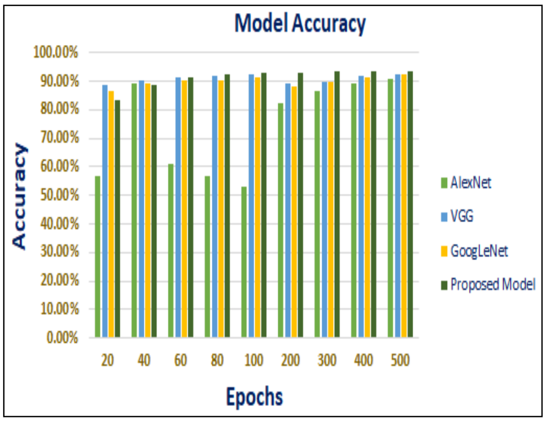

Fig:10 Accuracy comparison chart Lycopersicon crop leaf[46]

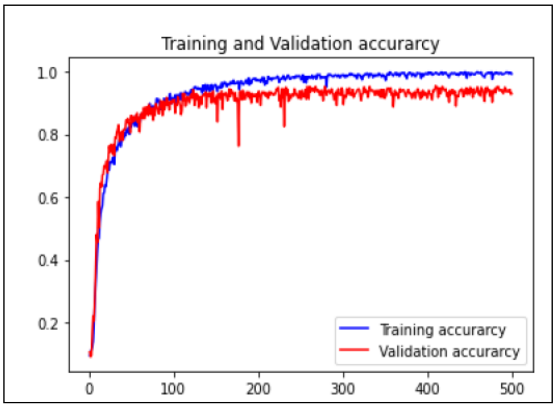

Fig:11 Training Testing accuracy for Night-CNN

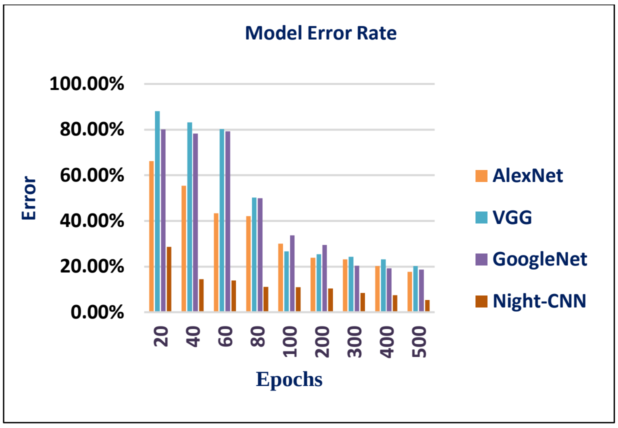

Fig:12 Error comparison chart of Models

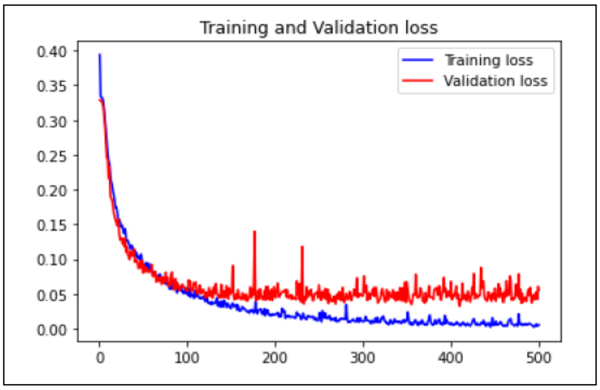

Fig:13 Training Testing Loss

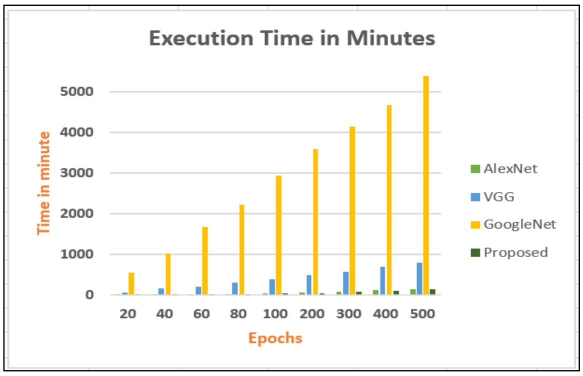

Fig:14 Time comparison with Night-CNN

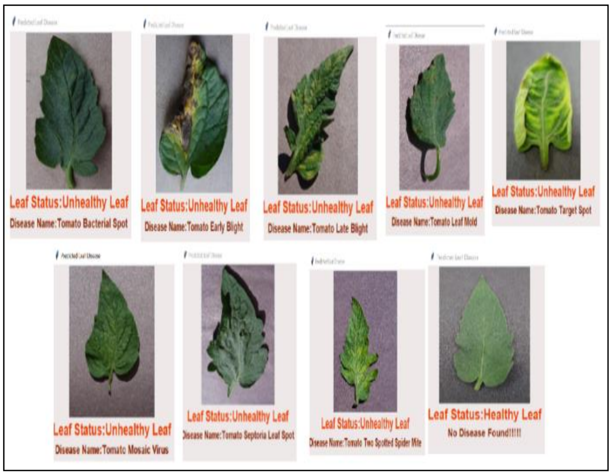

Fig:15 Classify Disease using Night-CNN[46]

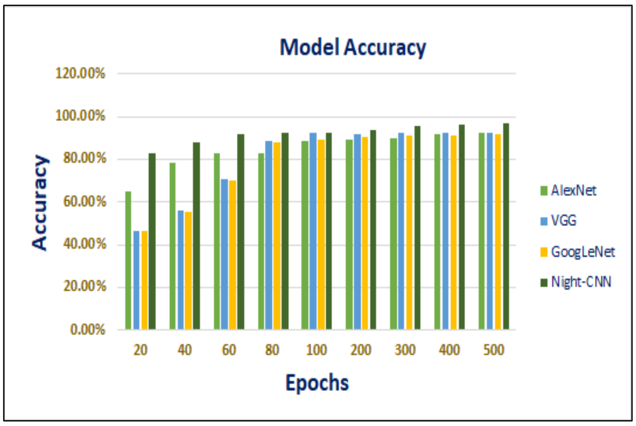

Fig:16 Model Accuracy comparison for Tuberosum and Capsicum

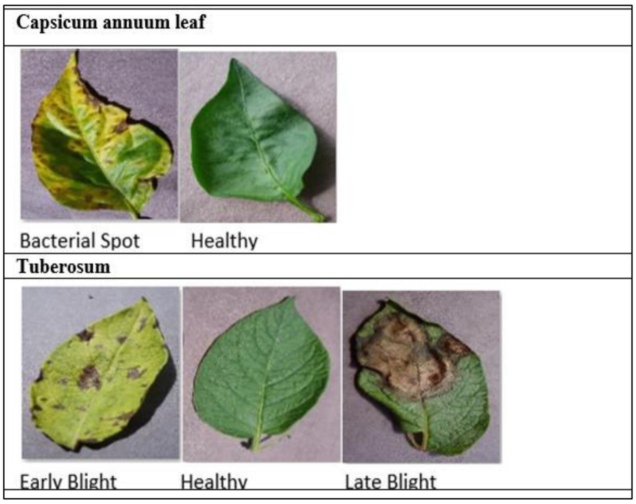

Fig:17 Identified the diseases of Tuberosum and Capsicum Leaf

Although the deep learning model requires a long time to train, the model, more resources and highly configured machines. The Night-CNN uses the single fully connected layer so it generates the least number of parameters. Due to less no of parameters, it requires comparatively less amount of time than the other three models. Figure 14 describes the time comparison chart over AlexNet, VGG, and GoogleNet. The model has been tested on the testing dataset. Figure:15 and figure 17 displayed the leaf disease has been identified by python application of Lycopersicon, Tuberosum and Capsicum Annuum crop leave test data. All diseases are classified based on their symptoms.

5. Conclusion

The research work has been proved that the Night-CNN gives remarkable results. The Night-CNN training and testing accuracy is almost 93% to 95%. The model accurately identifies healthy and unhealthy leaves. The model also classifies the unhealthy disease name very accurately and suggests the treatment for the disease so that the same disorder will not occur in the nearer future. The model generates a 5% to 8% error rate. The result has been proved that the proposed Night-CNN generates less parameters than the other models, hence it requires less amount of recourse and less computational power.

6. Future Work`

Although the deep learning techniques are expensive and time-consuming, they give very remarkable results, hence the proposed Night-CNN algorithm will apply to the complex background and real images for disease identification.

Declarations

Funding – Not Applicable

Conflicts of interest - The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Ethics approval - Not Applicable

Consent to Participate – Not Applicable.

Consent for publication – Dataset images we have used from the plant village repository.

Availability of data and materials – PlantVillage repository was used for the laboratory dataset.

Code availability- Proposed CNN models has been implemented in python with the OpenCV environment and executed on Google colab environment.

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