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Cotton Leaf and Plant Disease Identification using Intelligent Deep Learning Technique

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Abstract: India has the second-largest population and a vast range of crops. Most farmers produce cotton because it's lucrative, but cotton leaf disease has caused widespread crop failure and reduced farmers' income and quality of life in recent decades. Cercospora, Bacterial blight, Ascochyta blight, and Target spot may affect cotton leaves. Farmers' broad-brush assessments may be expensive and inaccurate. Cotton Leaf Disease Early diagnosis is difficult for farmers. If crops are infected early, farmers and crops will suffer. Farmers grow disease-free crops. Visual assessments of cotton leaf life are often inaccurate. A deep learning-based technique analyses plant leaf images to detect disease and estimate cotton quality. Uploading a photograph produces a digital, colour image of a damaged leaf. The picture will be processed using the proposed CNN to predict cotton leaf sickness. The technique aims to produce agricultural disease-detecting technology. The user uploads a sick leaf digital colour picture to start image processing. Finally, CNN can forecast illness. Plant disease diagnostics may avoid a pandemic. Fungi, bacteria, and viruses commonly kill plants. Farmers used their sight to spot illness. This study recommends early agricultural disease detection and fast action to reduce crop losses. Cotton productivity plummets due to disease. We're studying the cotton leafand plant. Alternaria, Cercospora, Red, White, and Yellow Spots on the Leaf cause 90–99% of cotton leaf diseases. The technique is 99.67% effective.

Keywords: *Crop, Cotton, CNN, Agricultural Disease, Cotton Leafand Plant, Cotton Leaf Diseases*

1. Introduction

According to the Observation in India, India is mostly an agricultural nation. The majority of the population is involved in agricultural activities. Farmers may choose from a wide variety of crops that are suited to their farm's thanks to the availability of this variety. However, to ensure the highest possible output and quality of products, the cultivation of these crops often requires a high level of expertise. Because most of the key signs of the illness are minute, human visual skills are a challenge when attempting to diagnose it. This technique is laborious and takes a considerable amount of time. Identifying the signs and symptoms of disease using some image processing is now one of the most pressing issues facing researchers in the field of medicine. The farmers are searching high and low throughout their daily lives for a remedy that can cure the sickness that affects the cotton leaf. Farmers have a pressing need for a disease diagnostic system that would help them. Processing digital photos that have been obtained of the plant's leaves allows for disease detection to be the primary emphasis of this method.

This research uses a system that detects cotton leaf illnesses by implementing a Convolutional Neural Network. It provides methods that are better capable of discovering infections caused by bacteria and the influences of the environment. Farmers have a difficult challenge when trying to identify diseases early on in the growth cycle of their crops since this requires their presence. The spotting and identification of diseases on the crop are of critical significance. KNN, SVM, Random Forest, Artificial Neural Networks, and CNN are some of the algorithms that may be used in image processing for illness detection via picture categorization. In the past, image classification algorithms such as face recognition needed to pay attention to where the face was situated in an image. CNN can circumvent this key obstacle by processing aspects of an image in greater depth at each layer. Each kind of illness that might affect a crop has its unique characteristics, which can be retrieved at each layer of a convolution network.

The development of a system that can identify illnesses that affect crops is the objective of this application. Image processing begins with the digitized colour picture of the sick leaf being uploaded by the user into the system. This image is then used to diagnose the condition. Finally, by using CNN, it is possible to forecast plant diseases.

The primary objective of this research is to propose and build a generic model for properly diagnosing leaf diseases. The purpose of this research is to develop a model using Deep Learning that is capable of providing generalizations.

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The remaining parts of the research article are laid out as follows. The literature work is discussed in Section 2, which follows. The proposed work is presented in Section 3. Section 4 provides Implementation. The findings are discussed in Section 5, and the survey is wrapped up in Section 6.

2. Literature Work

The complexity of cotton crop production rose due to using the naked eye to detect these illnesses, reducing the accuracy in identification precision. Even a trained professional would be unable to tell what's wrong with the cotton plants just by looking at them, and this inefficient method results in more wasted products. These erroneous beliefs lead people to use pesticides that are harmful to healthy cotton, even though they are usually unneeded. A country's GDP will suffer even if farmers leave for a short period of time.

Researchers provided the following sets of research questions after giving thought to the concerns identified in the statement of problems:

First 1 : What method is best for identifying cotton pests and diseases?

Second 2: how can we create a fully automated system to identify and track cotton-related pests and diseases?

Question 3: What factors into deciding a model's purchase?

The combination of picture processing and data analysis consist

utes deep learning opens up a wider range of potential results. This useful tool has progressed into the agricultural sector. Several modern computer vision applications rely on deep learning to achieve impressive results. These include CNN (convolutional neural network), RNN (recurrent neural network), DBN (deep belief network), and DBM (deep Boltzmann Machine). However, CNN stands out as this study's most significant use case [8]. These days, we employ CNN methods to create automated diagrams of instructions for analysis [9] and to recognize various objects. Recently, the K-fold cross-validation approach was suggested for partitioning datasets and improving CNN model generalization. In most cases, the final model was constructed from scratch rather than being a derived or transferred learning model. The promise of human intervention data [10] has attracted interest in using deep learning to optimize performance while classifying various activities. The use of deep learning for understanding brain activity has recently attracted much attention in the real world [11]. Electroencephalogramsignals, native access for attention-based bidirectional long-short-term memory, are prone to intertrial and intersubject fluctuation. The electroencephalogram (EEG) imaginal motor functions were studied using a convolutional neural network and found to be affected by four distinct parameters. Here, feature extraction from raw EEG data was made possible by combining bidirectional long-short-term memory with the attention model. Improvements in the clinical translation of electroencephalogram(EEG) motor imaginary (BI)-based brain-computer interface technology are appropriate for a wide range of requests; this system helps those who are paralyzed. The greatest accuracy and time-resolved forecasts [12] are among the extraordinary accomplishments of 'e. Humans play a crucial part in developing successful interface systems. To discern the four-class motor imagined intents by mutual agreement through the similarity of electroencephalogramelectrodes, an unique deep learning framework called graph convolutional neural networks was developed to meet the problems. Predictions for the motor imaginary are most reliable when applied to four activities [13].

The model improved upon the accuracy of the original YOLOv3 model by 1.64% on an independently created dataset while simultaneously reducing the number of training parameters by 48.90%. The updated YOLOv3 model described in this article outperformed competing methods in detecting the growth sites of the main cotton stem over a wide range of light and complicated real-world situations [14].

When used to map crop kinds, this technique allows for the automatic extraction of the most prevalent crop types within a given area. Furthermore, this approach permits the extraction of outlying profiles, which may help uncover mislabeled time series [15] when used in a labeled setting.

The experimental findings reveal that the accuracy of ResNet50, VGG19, InceptionV3, and ResNet152V2 range from 75.76 percent to 87.64 percent, 96.4 percent to 98.36 percent, respectively. Because of this, the notion of using a transfer learning system called ResNet152V2 for plant disease detection is both practical and effective [16].

Farmers may identify afflicted plants with a single click of a picture and find out what treatment is needed. A simple, language-friendly method like this may greatly help farmers maintain the quality and quantity of their agricultural produce [17].

When used to crop-types mapping, this approach allows for the automatic extraction of the most prevalent crop kinds present in a given scene. This technique also permits the extraction of outlying profiles, which may help uncover mislabeled time series [18] in a classified setting.

Using FCN-8 s, CED-Net, SegNet, DeepLabv3, and U-Net for semantic segmentation and the CRF approach for allocating disease sections in leaf crops, the authors propose an effective IoT-based plant disease identification system. We will assess this network's performance and compare it to other state-of-the-art networks. The F1-score, sensitivity, and intersection over union are proclaimed by the experimental outcomes and their comparisons (IoU). Compared to existing approaches, the suggested system using SegNet and CRFs achieves excellent results. Experimental evidence supports the superiority and efficacy of the improvement above strategy and its broad applicability [19].

In terms of intensity fluctuations, colour changes, and variances identified in the shapes and sizes of leaves, the PlantVillage Kaggle database is the gold standard dataset for plant illnesses and problems. Quantitative and qualitative research indicates that the provided strategy is more effective and trustworthy than other recent methods [20] in identifying and classifying plant diseases.

The research employed hyperspectral images for plant disease diagnosis is also summarised, as are the diverse data sources used by these investigations. This publication [21] also discusses the difficulties presently encountered in establishing a plant disease detection system and the gaps and unexplored territories in this field.

The widespread availability of cellphones plays a crucial role in diagnosing plant diseases. Plant disease detection may be made more efficiently and at a lower cost using automated pictures and mobile phone cameras. The accuracy of 10 previously-trained models was assessed in this work by applying transfer learning to our dataset of cotton plants [22].

Using photos of both diseased and healthy cotton leaves, a deep convolutional neural network (CNN) model is created to detect cotton plant diseases. The constructed model was tested to ensure its efficacy, and the results confirmed that the new system was cost-effective and decentralized. This work presents a novel approach for researchers interested in establishing a cotton plant disease identification system [23], which allows for the most precise and efficient disease diagnosis and control in cotton plants to date.

Table 1. Literature Work

Author	Methodology	Crop	Type of the Disease	Limitation
[24]	Image Processing	Cotton	Leaf Spot	The author asserts without proof that this work may be a universal method for diagnosing any ailment.
[25]	Decision Tree Classifier	Cotton	Cotton Disease	In the suggested study, the author employs several factors, including temperature, soil moisture, etc., to foresee the onset of cotton disease. The author employs a decision tree classifier for categorization. Plant diseases cannot be detected solely using soil, moisture, and temperature as determining factors.
[26]	Image Segmentation, Gaussian filter, Graph cut	Cotton	Leaf Spo	To detect cotton diseases, the author has employed manual image processing techniques.

				The approach is time-consuming since it relies on image processing.
[27]	CNN	Cotton	Flower species	The author's research on cotton flower species has used photographs captured by unmanned aircraft.
[29]	CNN, VGG16 Transfer Learning, ResNet50, GoogLeNet	Cotton	Healthy, Leaf Spot, Target Leaf Spot, Powdery Mildew Nutrient Deficiency, Verticillium wilt, Leaf curl	The suggested model by the author has an accuracy of 98.53%, however, one of the limitations is that it requires a long processing time before it can be deployed.
Proposed work	ResNet152	Cotton	diseased cotton leaf , diseased cotton plant, fresh cotton leaf , fresh cotton plant	

3. Proposed Work

The suggested system utilizes the image classification method CNN to determine the kind of leaf it looks at. It can automatically detect and identify illnesses using the information derived from each convolution layer.

Algorithm:the cotton dataset is imbalanced in terms of the number of samples per class, so the algorithm begins with the argument that the class has fewer samples. Then,once the dataset is prepared algorithm extracts features from the dataset using Resnet152v2 for feature extraction; once features are extracted, the algorithm uses channel attention to separate the regions from the data then every region is processed and converted into regular shapes regions. Max pooling is applied to select regions of interest until all regions explored FASTERCNN with modified parameters called over regions and softmax layer parallelly make classification and stored into a list which reruns by the algorithm in the end.

```
Proposed algo(dataset, class lebel)
  {
      For data set D.agument // augmenting dataset images using torch library

      F= apply pertained Resnet152v2 (D) // resnet152v2 from torch returns features

      R=Apply channel wise attention (F) // using a torch. Vision returns regions R

      For each region R:

      R=R.RPN   // RPN converts all irregular shapes into constant

      R=R.MAXPOOLING // apply max pooling using a torch

      While(R!=Null)

      {
          //apply FASTRCNN using a torch to detect diseases infected regions from R

          R=R.softmax()

          Return class label

      }
}
```

Figure 1 demonstrates the structural design of the system that was proposed. The method of illness identification used this system's expertise in picture processing. The picture of the cotton plant leaf has to be uploaded by the user. The system can pre-process the picture uploaded and then apply the CNN algorithm. The system can test the picture with the training dataset thanks to the CNN approach and extract the features.

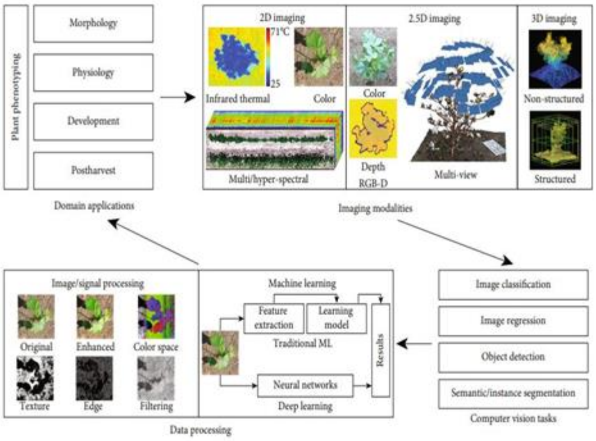

Fig 1: Process of proposed work.

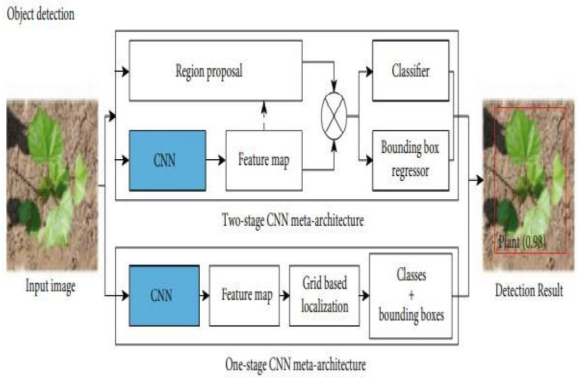

Fig 2: Process of Semantic/ instance segmentation.

Figure 2 shows semantic and instance segmentation. The first step was image was taken, then encoder-decoder based on the proposed method.Finally, output finds two-step first semantic and second instances.

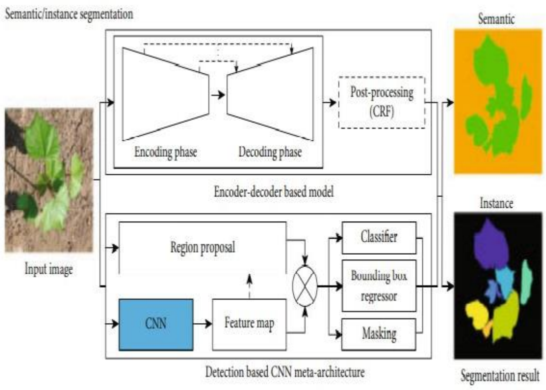

Fig 3: Process of Object detection.

Figure 3 shows Object detection. The first step image was to take, then apply two stagesof CNN meta-architecture based on the proposed method.Finally,the output gets detection of leafs and plants.

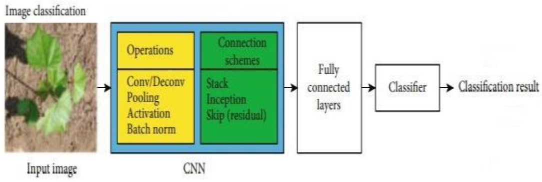

Fig 4: Process of image classification.

Figure 4 shows image classification. The first step image was to take thatfirst step to apply operations like Conv/deconv , pooling, activation batch norm, second step connection schemes, and lastly, apply fully connected layers with classifier for disease.

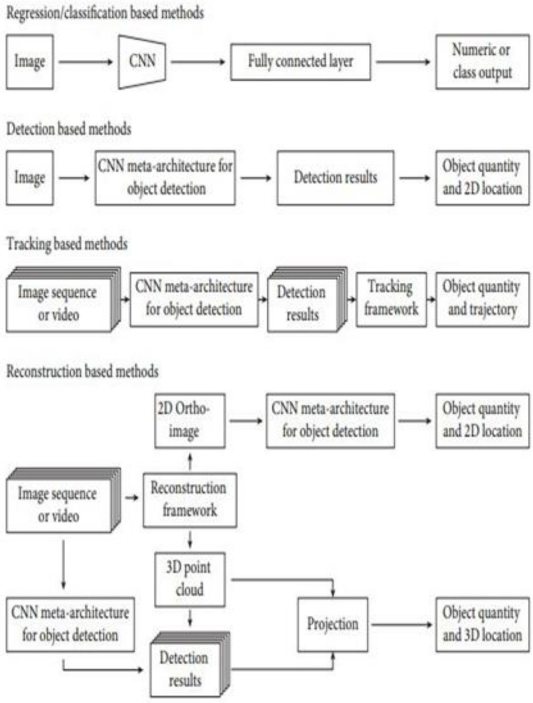

Fig 5: Proposed step-wise methods.

Figure 5 shows the Proposed step-wise methods; the model is divided into three parts first, detection-based methods, second tracking-based methods, and third reconstruction-based methods.

Layer (type)	Output Shape	Param #
conv2d_4 (Conv2D)	(None, 146, 146, 32)	2432
conv2d_5 (Conv2D)	(None, 142, 142, 32)	25632
max_pooling2d_2 (MaxPooling2	(None, 71, 71, 32)	0
dropout_3 (Dropout)	(None, 71, 71, 32)	0
conv2d_6 (Conv2D)	(None, 69, 69, 64)	18496
conv2d_7 (Conv2D)	(None, 67, 67, 64)	36928
max_pooling2d_3 (MaxPooling2	(None, 33, 33, 64)	0
dropout_4 (Dropout)	(None, 33, 33, 64)	0
flatten_1 (Flatten)	(None, 69696)	0
dense_2 (Dense)	(None, 256)	17842432
dropout_5 (Dropout)	(None, 256)	0
dense_3 (Dense)	(None, 4)	1028

Total params: 17,926,948
Trainable params: 17,926,948
Non-trainable params: 0

Fig 6: Configuration of the proposed method

4. Implementation

4.1 Hardware and Software

A full-screen, touch-enabled IPS panel measuring 14 inches in size that can be folded into the form factor of a tablet (the x360 Touchscreen 2-in-1). Python was used for this endeavor and a laptop that included a 10th-generation Core i7-10510U processor and a 512GB solid-state drive. The operating system of option was Windows 10 Home 64 Bit. Different kinds of processors include: The L3 cache is 8 MB, and the clock speed is 1.6 GHz. There are four processor cores, and the base frequency ranges from 1.6 GHz up to 4.9 GHz, thanks to Intel's Turbo Boost Technology. HD Audio and Intel Iris Plus Graphics are also included in this system. The HD TrueVision camera is available from HP. Python libraries such as NumPy, Pandas, SciPy, PyTorch and Plotly, Keras, and OpenCV-python were used in the method.

4.2 Dataset

We have collected data from open-source websites like kaggle.com. We'll look at thousands of photos of plant leaves with various class names. Our goal is to correctly identify cotton crop-disease relationship by using just the picture of the plant leaf as input. Before running the model optimization and predictions, we will downscale a cotton crop-disease pair from the PlantVillage dataset to 256*256 pixels. [28]

4.3 Model

4.3.1 Image Acquisition / Image Extraction: The photos of the damaged plant are collected by the High-Resolution camera, and the resulting image will be in RGB format (red, green, and blue). During the picture capture process, the colour conversion for an RGB image of a leaf will be completed. In order to get rid of the noise that was introduced throughout the process of acquiring the leaf picture, object removals were carried out. The Image pre-processing approach is utilized to extract the primary leaf picture area, and other sections of the image will be clipped. This is done in preparation for the image clipping.

4.3.2 Pre-processing of Images and Labeling of Features: Finding the illness affecting the plant in its early stages is the most important step in mitigating any loss that might occur to the agricultural product's quality or quantity. The data contained inside a picture is enhanced before it is processed further. It eliminates the distortion and improves some key aspects of the picture, both of which are essential for the further processing that will take place. The labeling method will apply eighty percent of the data.

4.3.3 The Process of Segmenting Images:

Representing an image in a form that is easier to comprehend and more meaningful requires a technique known as image segmentation. The data obtained is partitioned into training and testing categories, with 80 percent of the dataset serving as a training and 20 percent as the testing set. In addition, another strategy for improving the quality of the training data and the testing data is to pre-process the dataset. This strategy involves trimming the pictures to 256 by 256 pixels and keeping the training-by-testing ratio at (80/20). Similarly, the image's backdrop has been broken up into sections for the leaves. As a result, we will not be considering this further step. CNNs can determine which aspects of a group of photos should be retained and which should be removed. This works quite effectively.

4.3.4 Classification: In the last step, the leaf is arranged in a certain order depending on the many categorization methods that are used in a neural network. After that, the data that has been segmented is input into the neural network model that has been presented for the categorization of pictures, and performance measures are utilized to assess various approaches. Finally, visualization methods and mappings are used to name the file and its delivery to identify and classify the disease-affected plant leaf of mango, potato, tomato, soybean, and grape. This is done to detect and classify the illness. A subfield of machine learning known as deep learning features ascending and descending tiers. The outcome of the level always determines the input for the subsequent levels before it. During the learning process, the deep neural network will automatically extract the characteristics of the input sample. Natural language processing, computer vision, and medical applications are some examples of possible applications. The Convolution Neural Network is a deep neural network that can recognize and categorize things with just a small amount of additional processing. Convolutional layers, pooling layers, and fully linked layers are the components of CNN. Dropout, activation functions. After several steps, the image's feature map is obtained before moving on to the next layer. The sample input is convolved with the filter by adding the pixel value of the sample input to the value of the window selected for the filter. This creates the effect known as "convolution." The results of the previous filter are stored inside convolutional layers and the current layer. These filters have weights and biases that need to be discovered by the user. The second layer is known as the pooling layer, and it is during this layer the dimensions of the output matrix obtained from the previous levels of convolution are decreased. Max pooling and global pooling are two examples of possible approaches. During max pooling, a feature map with dimensions of 4 by 4 is reduced to 2 by 2, with each of the four components replaced by a single element. Pooling helps decrease the dimensions of an issue, the amount of computing required, the amount of overfitting that occurs, and the model's tolerance for changes and distortions. In a convolutional neural network (CNN), an activation function is a mechanism utilized to help the classifier grasp the complicated patterns present in the input dataset. If the feature map's input values are comprised of negative values, the Rectified Linear Unit (ReLU) function will reset those values to zero. It contributes to the process of making the model nonlinear. The amount of work done does not decrease due to this procedure. After an activation procedure, the most recent matrix produced is used as a completely linked layer input. In this section, the identification and classification processes necessary to compute the scores are carried out. The output of the completely linked layers is used as an input in the classification process.

The rectified linear activation function, often known as ReLU for short, is a piecewise linear function. If the input is positive, the function will produce the output directly; if the input is negative, the function will produce zero. Because a model that employs it is simpler to train and often produces superior results, it has evolved to the point where it is the activation function of choice for many different neural networks.

Why should you make advantage of pooling layers?

Softmax: A neural network cannot exist without its activation function; it is an essential component. A neural network is reduced to a straightforward linear regression model without an activation function. This indicates that the activation function provides the neural network with non-linearity.

- Pooling layers may be utilized to make the feature maps' files smaller. As a result, the network must do fewer calculations, and fewer parameters must be learned.
- The convolution layer's feature map is formed by a pooling layer, which summarises the properties in a certain area. This indicates that future operations are carried out on the summed-up features rather than the precisely positioned features produced by the convolution layer. As a result, the model is more resistant to changes in the placements of the features in the input image.
- One of the fundamental constituents of a Neural Network is called the activation function.
- Acquire an understanding of the operation of the Softmax activation when applied to a multiclass classification issue.

Dropout: The term "dropout" refers to the data or noise that is purposefully removed from a neural network to speed up processing and get results more quickly.

Table 2 : Hyperparameter of Proposed and Existing Method

Hyperparameter	Proposed	Existing [29]
Conv3 depth	8	4
Conv4 depth	36	32
Pooling	avg	max
Learning Rate	0.001	0.001
Optimizer	adam	adam
Accuracy	99.67%	98.53%
No. of Epochs	100	100
Dropout	0.12	0.25
Batch Size	32	32
Input Shape	256*256	224*224

Table 2 compares the hypermeters of the proposed model with the existing one, it's observed from the table that the proposed model has more layers of type conv3 and 4, but the average function used on pooling with the same learning and leads accuracy improved while keeping the same number of epochs and dropout is about 0.12 with batch size 32, and input shape more than base work.

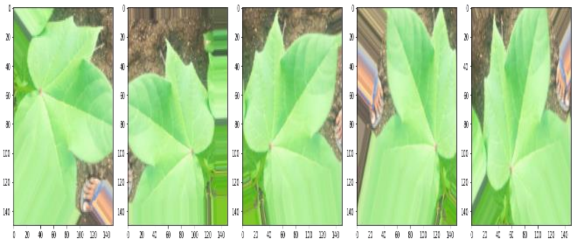

Fig 7. An illustrative example of the proposed method

5. Result

In this section, we have to explain the result in model accuracy and model loss and show the number of traning images and the number of validation images.

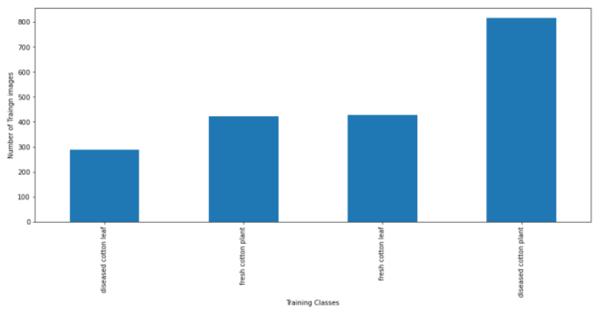

Fig 8. Shows Training classes concerningseveral training images.

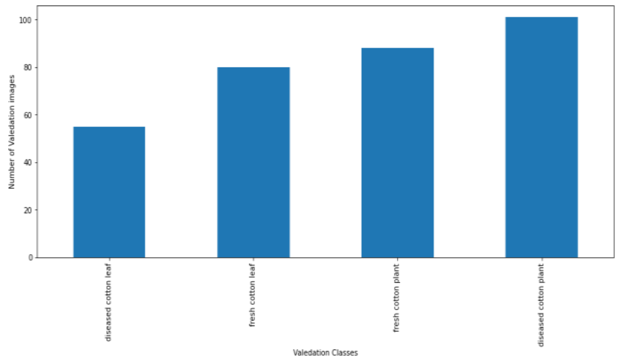

Fig 9. Shows validation classes concerningseveral validation images.

Figure 8 represents the distribution of classes over the dataset and the number of samples per class. Figure 8 shows the represented numbers for the training dataset in which

The fresh and diseased numbersare represented on the x-axis of the graphs; it's visible from the graphs that the initial dataset used needs to be augmented to balance the number of classes.

Figure 9 represents the distribution of classes over the dataset and represents the number of samples per class; figure 9 shows the represents numbers for the validation dataset in which

Fresh and diseased numbersare represented on the x-axis of the graphs; it's visible from the graphs that the initial dataset used needs to be augmented to balance the number of classes.

Fig 10. Shows validation classes concerningseveral validation images.

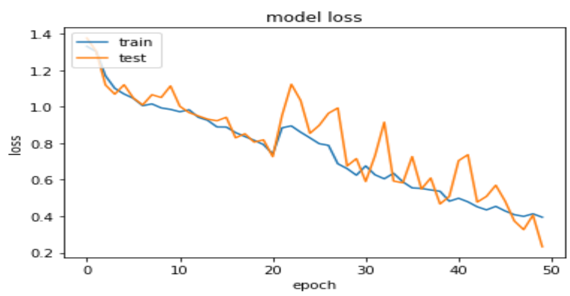

Fig 11. Shows validation classes concerningseveral validation images.

Figure 10 and 11 represent training and validation scores on each epoch which is visible that loss on your axis is kept deceased on every epoch and reachesa constant level even if increased the epochs; graphs also show that the model has neither high bais nor high variance which means it manages to maintain bias and variance trade of which makes results stable and better.

Table 3. Comparison of a Proposed Model with Existing Model Accuracy

S. No.	Model	Accuracy (%)	Dataset
1	Custom CNN [29]	95.37	Cotton
2	VGG16 [29]	98.1	Cotton
3	ResNet50 [29]	98.32	Cotton
4	Meta Deep Learn [29]	98.53	Cotton
5	Proposed Model	99.67	Cotton

Table 3 compares the performance of various models and shows that the proposed model achieves significant accuracy improvement over base models on the same dataset.Parameter tuning and management of layers in conv3 and conv4 make improvements possible, which separates the classes better than in previous models.

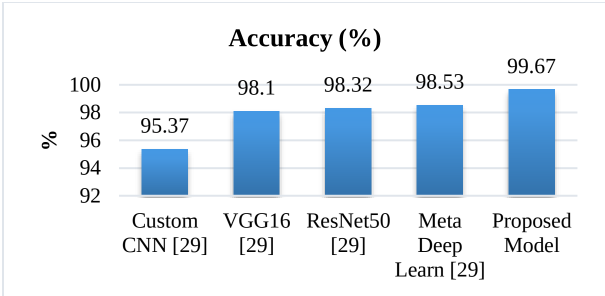

Fig 12. Comparison of the Proposed model with existing model accuracy

Figure 12 plots the visual representation of the above table and shows that accuracy values are increasing as we move towards least recent to most recent works and highest in the proposed work. Which rambles that the proposed model avoids overfitting, making it better in terms of results stability.

6. Conclusion

To take preventative steps at the earliest feasible stage, the algorithm will assist the end user in separating the diseased crop according to the proportion of infection present. The algorithm will assist in reducing the number of pesticides used, consequently contributing to an improvement in the environment and the ecological balance. The suggested research offers a wide range of applications that may assist Indian farmers in detecting illnesses affecting cotton crops early.

We can extend the illness dataset to identify additional diseases in the future. Work on accuracy that may enhance user results and provide the user with the appropriate pesticides or insecticides. In addition, we created the app to be mobile-friendly, so all of the processing is done in the cloud. That one item may be useful to the user since the procedure can be carried out on any device that the user has.

7. Test Result After Trained Model

In this section, we have to display the model-tested results and tested two different images fresh cotton plant and a diseased cotton leaf. When inputting both images sequentially, the model shows whether a plant or leaf of cotton was detected as a disease.

Fig 13 . Test result after trained model.

References

[1] S. Maity, C. Patnaik, M. Chakraborty and S. Panigrahy, "Analysis of temporal backscattering of cotton crops using a semiempirical model," in IEEE Transactions on Geoscience and Remote Sensing, vol. 42, no. 3, pp. 577-587, March 2004, doi: 10.1109/TGRS.2003.821888.

[2] Z. Xu, M. A. Latif, S. S. Madni, A. Rafiq, I. Alam and M. A. Habib, "Detecting White Cotton Bolls Using High-Resolution Aerial Imagery Acquired Through Unmanned Aerial System," in IEEE Access, vol. 9, pp. 169068-169081, 2021, doi: 10.1109/ACCESS.2021.3138847.

[3] M. A. Lee, Y. Huang, H. Yao, S. J. Thomson and L. M. Bruce, "Determining the Effects of Storage on Cotton and Soybean Leaf Samples for Hyperspectral Analysis," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 7, no. 6, pp. 2562-2570, June 2014, doi: 10.1109/JSTARS.2014.2330521.

[4] C. Santos and A. Riyuiti, "The Use of Agroxml Standard for data exchange processes in the Cotton Culture," in IEEE Latin America Transactions, vol. 10, no. 1, pp. 1425-1427, Jan. 2012, doi: 10.1109/TLA.2012.6142496.

[5] X. Jin, Z. Li, H. Feng, X. Xu and G. Yang, "Newly Combined Spectral Indices to Improve Estimation of Total Leaf Chlorophyll Content in Cotton," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 7, no. 11, pp. 4589-4600, Nov. 2014, doi: 10.1109/JSTARS.2014.2360069.

[6] L. Xun, J. Zhang, D. Cao, S. Zhang and F. Yao, "Crop Area Identification Based on Time Series EVI2 and Sparse Representation Approach: A Case Study in Shandong Province, China," in IEEE Access, vol. 7, pp. 157513-157523, 2019, doi: 10.1109/ACCESS.2019.2949799.

[7] R. Priya, D. Ramesh and V. Udutalapally, "NSGA-2 Optimized Fuzzy Inference System for Crop Plantation Correctness Index Identification," in IEEE Transactions on Sustainable Computing, vol.

7, no. 1, pp. 172-188, 1 Jan.-March 2022, doi: 10.1109/TSUSC.2021.3064417.

[8] Wang, G.; Sun, Y.; Wang, J. Automatic Image-Based Plant Disease Severity Estimation Using Deep Learning. Comput. Intell. Neurosci. 2017, 2017, 2917536.

[9] Saleem, M.H.; Potgieter, J.; Arif, K.M. Plant disease classification: A comparative evaluation of convolutional neural networks and deep learning optimizers. Plants 2020, 9, 1319.

[10] Yan, Q.; Yang, B.; Wang, W.; Wang, B.; Chen, P.; Zhang, J. Apple leaf diseases recognition based on an improved convolutional neural network. Sensors 2020, 20, 3535.

[11] Khan, M.A.; Akram, T.; Sharif, M.; Awais, M.; Javed, K.; Ali, H.; Saba, T. CCDF: Automatic system for segmentation and recognition of fruit crops diseases based on correlation coefficient and deep CNN features. Comput. Electron. Agric. 2018, 155, 220–236.

[12] Hughes, D.P.; Salathe, M. An Open Access Repository of Images on Plant Health to Enable the Development of Mobile Disease Diagnostics. 2015. Available online: http://arxiv.org/abs/1511.08060 (accessed on 15 November 2021).

[13] Liakos, K.G.; Busato, P.; Moshou, D.; Pearson, S.; Bochtis, D. Machine learning in agriculture: A review. Sensors 2018, 18, 2674.

[14] C. Wang, S. He, H. Wu, G. Teng, C. Zhao and J. Li, "Identification of Growing Points of Cotton Main Stem Based on Convolutional Neural Network," in IEEE Access, vol. 8, pp. 208407-208417, 2020, doi: 10.1109/ACCESS.2020.3038396.

[15] T. Di Martino, R. Guinvarc'h, L. Thirion-Lefevre and É. C. Koeniguer, "Beets or Cotton? Blind Extraction of Fine Agricultural Classes Using a Convolutional Autoencoder Applied to Temporal SAR Signatures," in IEEE Transactions on Geoscience and Remote Sensing, vol. 60, pp. 1-18, 2022, Art no. 5212018, doi: 10.1109/TGRS.2021.3100637.

[16] P. Sivakumar, N. S. R. Mohan, P. Kavya and P. V. S. Teja, "Leaf Disease Identification: Enhanced Cotton Leaf Disease Identification Using Deep CNN Models," 2021 IEEE International Conference on Intelligent Systems, Smart and Green Technologies (ICISSGT), 2021, pp. 22-26, doi: 10.1109/ICISSGT52025.2021.00016.

[17] L. Saraswat, L. Mohanty, P. Garg and S. Lamba, "Plant Disease Identification Using Plant Images," 2022 Fifth International Conference on Computational Intelligence and Communication Technologies (CCICT), 2022, pp. 79-82, doi: 10.1109/CCiCT56684.2022.00026.

[18] T. Di Martino, R. Guinvarc'h, L. Thirion-Lefevre and É. C. Koeniguer, "Beets or Cotton? Blind Extraction of Fine Agricultural Classes Using a Convolutional Autoencoder Applied to Temporal SAR Signatures," in IEEE Transactions on Geoscience and Remote Sensing, vol. 60, pp. 1-18, 2022, Art no. 5212018, doi: 10.1109/TGRS.2021.3100637.

[19] Rezk, N.G., Attia, AF., El-Rashidy, M.A. et al. An Efficient Plant Disease Recognition System Using Hybrid Convolutional Neural Networks (CNNs) and Conditional Random Fields (CRFs) for Smart IoT Applications in Agriculture. Int J Comput Intell Syst 15, 65 (2022).

[20] Albattah, W., Nawaz, M., Javed, A. et al. A novel deep learning method for detection and classification of plant diseases. Complex Intell. Syst. 8, 507–524 (2022). https://doi.org/10.1007/s40747-021-00536-1

[21] Joseph, D.S., Pawar, P.M. & Pramanik, R. Intelligent plant disease diagnosis using convolutional neural network: a review. Multimed Tools Appl (2022). https://doi.org/10.1007/s11042-022-14004-6

[22] Kumar, S., Musharaf, D., Sagar, A.K. (2022). Comparative Study of Pre-trained Models on Cotton Plant Disease Detection Using Transfer Learning. In: Shaw, R.N., Das, S., Piuri, V., Bianchini, M. (eds) Advanced Computing and Intelligent Technologies. Lecture Notes in Electrical Engineering, vol 914. Springer, Singapore. https://doi.org/10.1007/978-981-19-2980-9_12

[23] Patil, B.V., Patil, P.S. (2021). Computational Method for Cotton Plant Disease Detection of Crop Management Using Deep Learning and Internet of Things Platforms. In: Suma, V., Bouhmala, N., Wang, H. (eds) Evolutionary Computing and Mobile Sustainable Networks. Lecture Notes on Data Engineering and Communications Technologies, vol 53. Springer

[24] Parikh, A.; Raval, M.S.; Parmar, C.; Chaudhary, S. Disease Detection and Severity Estimation in Cotton Plant from Unconstrained Images. In Proceedings of the 2016 IEEE International Conference on Data Science and Advanced Analytics (DSAA), Montreal, QC, Canada, 17–19 October 2016; pp. 594–601.

[25] Chopda, J.; Raveshiya, H.; Nakum, S.; Nakrani, V. Cotton crop disease detection using decision tree classifier. In Proceedings of the 2018 International Conference on Smart City and Emerging

Technology (ICSCET), Mumbai, India, 5 January 2018; pp. 1–5.
[26] Rothe, P.; Kshirsagar, R.V. Automated extraction of digital images features of three kinds of cotton leaf diseases. In Proceedings of the 2014 International Conference on Electronics, Communication and Computational Engineering (ICECCE), Hosur, India, 17–18 November 2014; pp. 67–71.
[27] Xu, R.; Li, C.; Paterson, A.H.; Jiang, Y.; Sun, S.; Robertson, J.S. Aerial images and convolutional neural network for cotton bloom detection. Front. Plant Sci. 2018, 8, 2235.
[28] https://www.kaggle.com/datasets/janmejaybhoi/cotton-disease-dataset
[29] Memon, M.S.; Kumar, P.; Iqbal, R. "Meta Deep Learn Leaf Disease Identification Model for Cotton Crop". Computers 2022, 11, 102.
[30] Prof. Sagar Kothawade. (2020). Scale Space Based Object-Oriented Shadow Detection and Removal from Urban High-Resolution Remote Sensing Images. International Journal of New Practices in Management and Engineering, 9(04), 17 - 23. Retrieved from http://ijnpme.org/index.php/IJNPME/article/view/95
[31] Soundararajan, R., Stanislaus, P. M., Ramasamy, S. G., Dhabliya, D., Deshpande, V., Sehar, S., & Bavirisetti, D. P. (2023). Multi-channel assessment policies for energy-efficient data transmission in wireless underground sensor networks. Energies, 16(5) doi:10.3390/en16052285