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ORIGINAL

Disease Detection using Region-Based Convolutional Neural Network and ResNet

Detección de enfermedades mediante redes neuronales convolucionales basadas en regiones y ResNet

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ABSTRACT

In recent times, various techniques have been employed in agriculture to address different aspects. These techniques encompass strategies to enhance crop yield, identify hidden pests, and implement effective pest reduction methods, among others. Presented in this study a novel strategy which focuses on identification of plant leaf infections in agricultural fields using drones. By employing cameras on drones with high resolution, we take precise pictures of plant leaves, ensuring comprehensive coverage of the entire area. These images serve as datasets for Deep Learning algorithms, including Convolutional Neural Networks(CNN), Resnet, ReLu enabling the early detection of infections. The deep learning models leverage the captured images to identify and classify infections at their initial stages. The usage of R-CNN and ResNet technology in agriculture field has brought the tremendous change when we detect the disease in earlier stage of crop. Thus the farmer can take the pest preventive measures in the beginning stage to avoid crop failure.

Keywords: Resolution; Drones; Deep Learning; ResNet; Regional Convolutional Neural Network.

RESUMEN

En los últimos tiempos se han empleado diversas técnicas en la agricultura para abordar distintos aspectos. Estas técnicas abarcan estrategias para mejorar el rendimiento de los cultivos, identificar plagas ocultas y aplicar métodos eficaces de reducción de plagas, entre otras. En este estudio se presenta una novedosa estrategia centrada en la identificación de infecciones en hojas de plantas en campos agrícolas mediante el uso de drones. Mediante el empleo de cámaras en drones con alta resolución, tomamos imágenes precisas de las hojas de las plantas, asegurando una cobertura completa de toda la zona. Estas imágenes sirven como conjuntos de datos para algoritmos de aprendizaje profundo, incluyendo redes neuronales convolucionales (CNN), Resnet, ReLu que permiten la detección temprana de infecciones. Los modelos de aprendizaje profundo aprovechan las imágenes capturadas para identificar y clasificar las infecciones en sus fases iniciales. El uso de la tecnología R-CNN y ResNet en el campo de la agricultura ha supuesto un gran cambio al detectar la enfermedad en una fase temprana del cultivo. De este modo, el agricultor puede tomar medidas preventivas contra las plagas en la fase inicial para evitar la pérdida de cosechas.

Palabras clave: Resolución; Drones; Deep Learning; ResNet; Regional Convolutional Neural Network.

INTRODUCTION

In India agriculture sector contributes more GDP. Most of the people in India have occupation as agriculture. For these people yield of the crop plays a vital role for their livelihood. So we would like to make it easier for the such kind of people in producing more crop and reduces the chances of various damages that affecting the production of the yield. The best solution to improve agriculture sector is to integrate it with technology. We can use various types of technologies like Robotics, drones, Iot sensors, AI and many more. There are lot many technologies which can transform the agriculture sector in a better way.

The field of agriculture has witnessed a remarkable advancement in recent times, with the adoption of various techniques aimed at improving agricultural practices. These techniques encompass a wide range of strategies, including those focused on increasing crop yield, detecting hidden pests, and implementing efficient pest reduction methods. This paper introduces an innovative approach that specifically targets the identification of plant leaf infections in agricultural fields, employing drones equipped with high-resolution cameras. By leveraging the capabilities of drones, we capture detailed images of plant leaves, ensuring thorough coverage of the entire area under observation.

The captured images serve as valuable datasets for deep learning algorithms, such as Convolutional Neural Networks (CNN), ResNet, ReLu models. These algorithms play a crucial role in facilitating the early detection of infections, enabling timely intervention and preventive measures. With their ability to learn and extract meaningful features from the captured images, the deep learning models effectively identify and classify infections at their initial stages. This proactive approach allows farmers and agricultural experts to swiftly respond to potential outbreaks and mitigate the spread of diseases, thereby safeguarding crop health and productivity.

Furthermore, the results obtained from the application of deep learning techniques are seamlessly integrated into a cloud-based platform. This deployment ensures convenient accessibility to the disease detection outcomes for all users involved in agricultural practices. The cloud-based platform serves as a central hub, allowing farmers, researchers, and decision-makers to access the collected data, analyse trends, and make informed decisions regarding disease management strategies. This democratization of information empowers stakeholders in the agricultural sector to implement effective disease control measures, optimize resource allocation, and ultimately enhance productivity and sustainability in agriculture.

In essence, this approach not only advances the cause of disease control but also contributes to the optimization of resource allocation, promoting sustainability and productivity in agriculture. As we stand at the forefront of this agricultural revolution, the fusion of technology and data-driven decision-making promises to bring a new era of farming that is more efficient, responsive, and resilient than ever before. We would even more like to connect this detected information with cloud where the farmers will be notified with an alert message when the disease is detected in field as our future work.

METHODS

After doing many literature surveys we get know that to get the best result for any research, framing out the model is must.

So we begin the process with the development and discovering of a model for detecting leaf diseases in crops using modern technologies like machine learning and deep learning which supports image classification.

To make this model more reachable to farmers and to identify the leaf diseases in short span of time we employed other new technologies which aids our CNN model. Drones are used as a novel and powerful tool for data collection. Drones offer wide range of services in agriculture field. So here we want to make use of it for the aerial coverage of crop and collecting the images of crop from all the different positions. It offers a major advantage of accessing remote areas or large agriculture areas. Our model mainly consists of 6 major steps for detecting the diseases present in leaf and finding accuracy of model.

2.1 Data Collection and Acquisition:

In this process of detection, the Dataset is generated manually from the photos captured by drone from massive fields. Drone takes the pictures of the crop from all the directions of the field. In this initial stage we gather a comprehensive dataset of images as well as videos of crops using high resolution cameras integrated to the drone. They collect the data under various climatic conditions, lightening and at various growth stages of crop to make the model more robust and adaptable to real world situation. They contain combinations of different types of leaves which are in good condition as well as diseased leaves. Using object detection we remove unnecessary disturbances like soil, stems and crop produces like flowers and fruits, so that we can detect only the leafy part from the images collected by drone. These pictures are again segregated into diseased and non-diseased leaves using masking technique. Only diseased leaves are used for training and **2.2**

Object Detection Model:

Object Recognition is the machine learning process which is used to identify different types of objects present in a digital photograph. There are three major steps in object detection:

Image classification: Predict the type of class or item in a photograph.

Data : A picture containing single entity like photograph
Outcome: Class identifier
testing process.

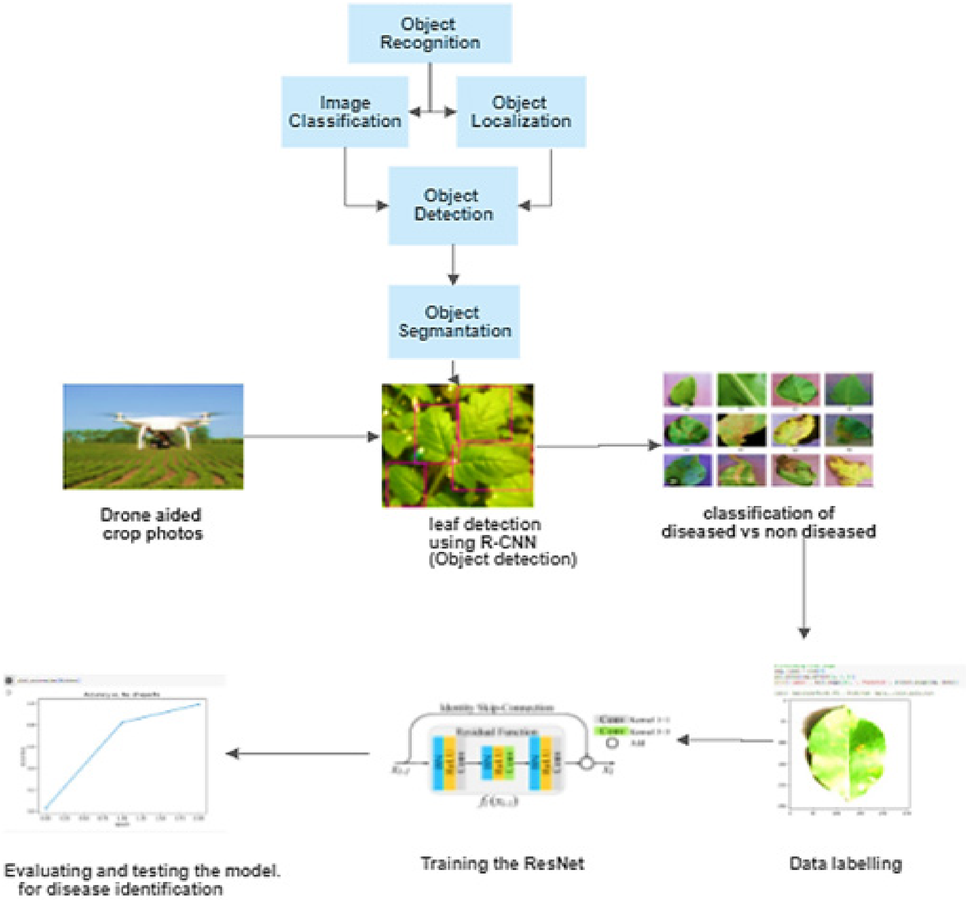

Figure 1. Steps for detecting the diseases present in leaf

Object positioning: Locating the count of entities present in a photograph using a enclosure rectangle.
Data: A picture containing single or multiple entities, like photograph.
Outcome: Single or multiple enclosure rectangles.

Object Recognition: Finding things in photo and labelling things what they are.

Here we achieved it using R-CNN machine learning model.

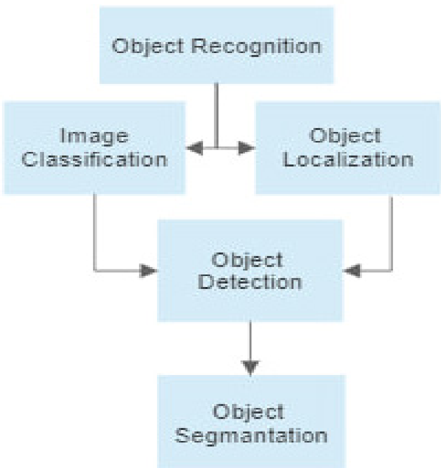

Figure 2. Detail process of step 2 in our customized model

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2.2.1 REGIONAL CONVOLUTIONAL NEURAL NETWORK(R CNN)

Let us consider an object recognition prototype containing a simple convolution network layer that contains the fully connected layers is not enough to detect the multiple objects present in the input image.

Our input contains many tea leaves in one particular image. So, to pick out one image of tea leaf that is either diseased or healthy, we must use region proposals.

1)Extraction of 2000 self governing territory recommendations for individual data. We use selective search algorithm proposed by Ross for selecting the region proposals. Region proposals are the small pictures combined together based on the color, shape and size of image and other distinguishing characteristics.

The selective search algorithm has three main steps in it:

a) Sub segmentation of images based on the characteristics like shape, size and color, texture.
b) Convert smaller bounding boxes into larger bounding boxes by combining the similar boxes in recursive way.
c) The larger boxes thus are converted to region proposals.

Application of CNN over region proposals

We need to opt a convolutional neural network model in this step to process the region proposals. We can opt any pretrained models like ResNet, AlexNet, ImageNet, DenseNet. We selected AlexNet for our experiment. We need to get 4096-dimensional feature vectors from each of the 2000 regions proposals extracted.

a) Model is fine-tuned to a specific task to be performed at the end. Here we fine-tune it to identify the classes of region proposals for detection of object.
b) To identify multiple leaves, present in one image we fine-tuned our AlexNet model by replacing the 1000 layer with soft max layer.

Input Size of AlexNet is (227,227,3). So, resize the region proposals to this dimensions so that they can fit into model. From this region proposal we get 4096 feature vectors. Our AlexNet consists of five convolutional layers & two fully connected layers.

Here we introduce a parameter f= the amount of possible dilation of bounding box.

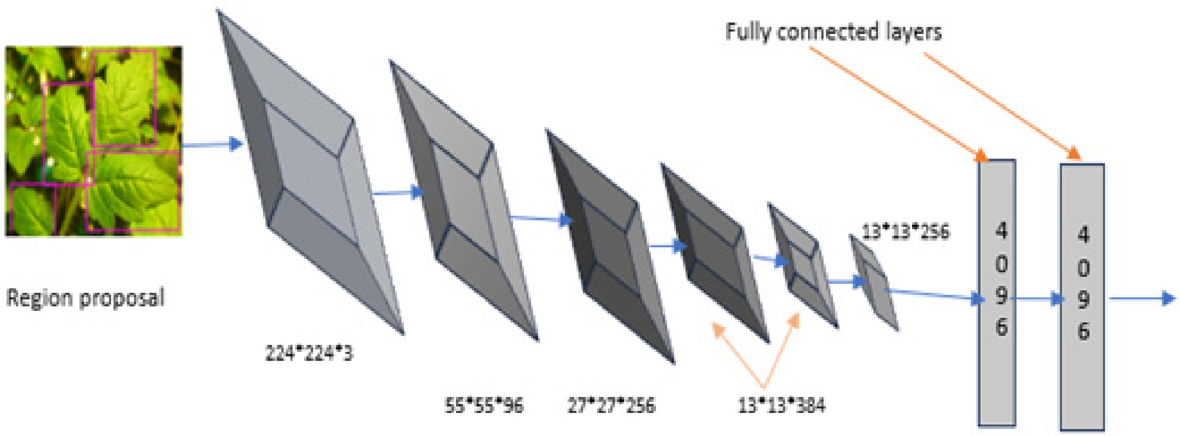

Figure 3. Convolution Neural network for object Identification

We will get “Feature vectors” after they passes through the fully connected layers.

3) the feature vectors obtained in step2 is then passed to a support vector machine. In this step training of support vector machine takes place. SVM trains on each individual classifier present in the feature vectors. After it gets trained it gives a confidential score for each of the feature vector it is taken as input. A normal CNN cannot perform this as it requires training of SVM and AlexNet parallelly at the same time. So we have opted R CNN and future versions like fast R CNN, faster R CNN. Every class has both positive and negative confidence scores. The features of all region proposals which are having Intersection over Union coexist beneath 0,3 and is surrounded with verified data box are considered to be negative. The features that simply contain the data box enclosure rectangle is estimated as beneficial for that class. Some of the region proposals that are ignored do not contain any ground truth boxes and IoU greater than 0,3.

The succession output of this stage is obtaining positive object proposals for each class from the CNN features obtained from 2000 region proposals.

4)Precise bounding box for each object present in the object proposals obtained from trained SVM. In this step4 we mainly we employee a linear regression technique called bounding box regression model for locating the plant leaves more precisely present in the image. For training this bounding box regression model we took four variables (a,b,c,h).

These are the dimensions of localization.

Where a= length of pixel of centre of bounding box.
b = breadth of pixel of centre of bounding box.
c= width of bounding box.
h=height of bounding box.
Let q=predicted proposal , s= target proposal.

Now we have to find the model to train the target transformation.

$Q = (q_{a,} q_b, q_c, q_h)$ ---------(1)
$S = (S_a, S_b, S_c, S_h)$ ---------(2)

Now perform ground truth transformation of above equations

$T_a = (s_a - q_a)/q_c$ --------- (3)
$T_b = (s_b - q_b)/q_h$ -------- (4)
$T_c = \log(s_c/q_c)$ ------- (5)
$T_h = \log(s_h/q_h)$ ------- (6)

The equations (3) & (4) denote the invariant translation of centre of grounding box q- a(x-axis) and b(Y-axis) coordinates.
The next 2 equations (5) & (6) denote the log space transformations of width c and height h.

$_x = Q_c d_a(Q) + Q_b$ --------- from (1) & (2)
$_y = Q_h d_b(Q) + Q_b$ --------- from (1) & (2)
$_w = Q_c \exp(d_c(Q))$
$_z = Q_h \exp(d_h(Q))$
= corrected predicted box done using original predicted box and the predicted transformation.
$d_k(Q)$ = predicted transformation; where k can be anything in a,b,c,h.
$d_k(Q) = w_k{}^t{}_5(Q)$
$w_k = \text{argmin} \sum_{i=0}^{n} (t^i{}_k - \widehat{W}_k{}^t \emptyset_5(Q^i))^2 + \text{lambda}(||w_k{}^t||^2)$ -------(7)

The predicted transformation $d_k(Q)$ is modelled as a linear pool function feature

-- $_5$ == it is dependent on the actual image features.
w_k == least square objective function

Bounding box regressor method increases the mean average precision of the result by 3 to 4 %. We can also increase the accuracy of result by removing the extra bounding boxes by using a non-maximum suppression. In this non maximum suppression, we remove the object proposals which are less value than threshold value which is 0,5.

The implementation of R CNN is little bit complex to implement as we need to train triple diverse patterns individually (CNN, SVM, Enclosure rectangle predictor).

2.3 Preprocessing and Annotation:

Before feeding the data into our model we need to preprocess the images collected by our drone. This preprocessing of data involves resizing the images, labelling the data images, analyzing the different types of information like length and width of images. This step also annotates the dataset by marking areas of healthy and diseased leaves.

Considering the below fig-4 the dataset is represented using a bar chart to enhance comprehension,here is the bar chart that represents the entire dataset that is being considered.

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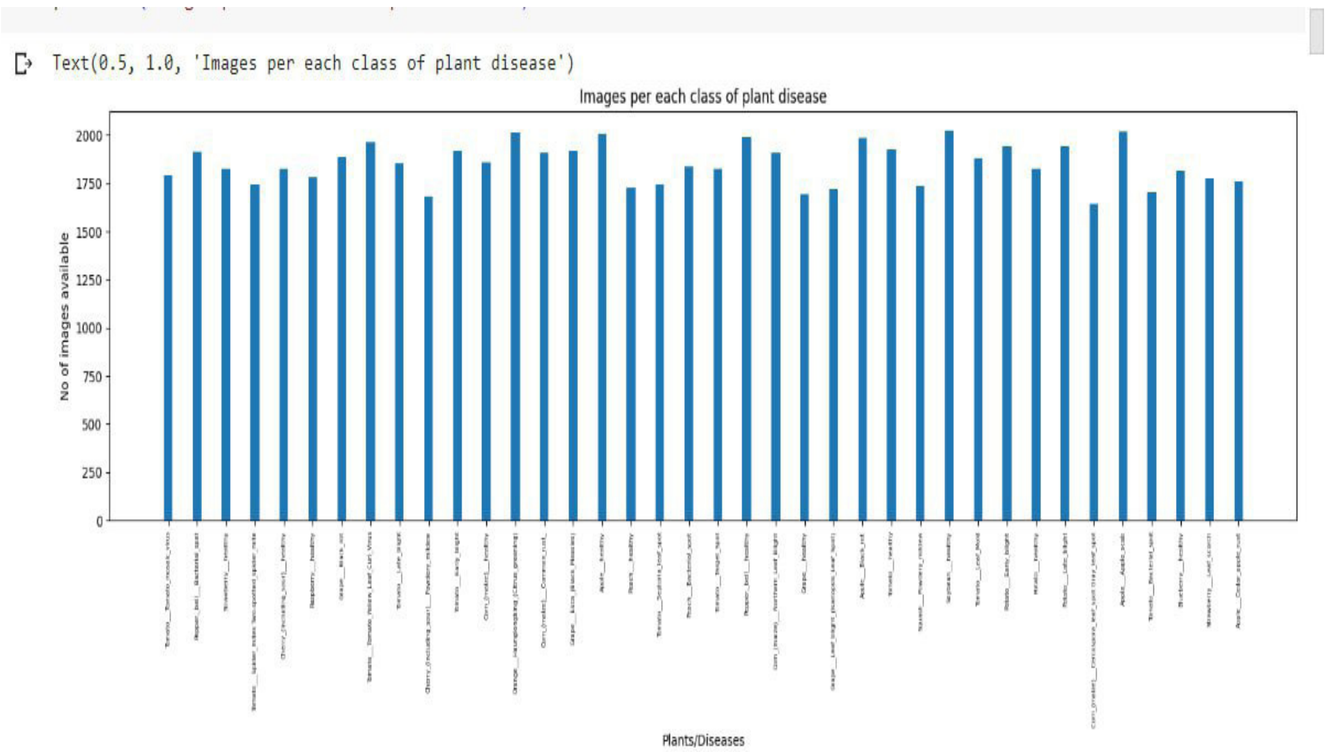

Figure 4. Data visualization of number of images available for each class of plant disease

2.4 Disease Detection Model:

Now employee a machine learning model to detect the disease present in an image. The above dataset has been divided into categories. half is training and another is testing.

We use ResNet model among image classification. Below fig-4 represent the structure of plant leaf disease is predicted by using ResNet prototype has been described below.

1.1.1 ResNet:

ResNet stands for Residual Network. It is a deep neural network architecture designed to train very deep networks effectively. It introduces residual blocks, which enable the learning of residual functions, allowing framework to handle gradient disappearance issues. ResNet is prominently used in computer vision activities such as picture categorization, object recognition, and scene parsing. Its ability to extract intricate features and its role in transfer learning make it a fundamental choice in various applications, significantly advancing the field of computer vision.

We use ResNet to identify plant leaf diseases for depth, transfer learning capabilities, robustness, and high accuracy make it a powerful choice for identifying plant leaf diseases from images, where the ability to extract and discriminate complex features is crucial for accurate diagnosis and crop management.

In order to avoid this loss and damage we use ResNet from CNN in deep learning techniques. In this we implement the ResNet in python by using freely accessible such as google collab which is intuitive. During this phase of identification, we initially introduce python libraries like numpy, pandas, matplotlib, touch, touch vision etc . Later we import the dataset file for the further process

1.1.2 GPU & CUDA(version 11.8):

We used Tesla T4 GPU and CUDA Version 11.8 to enhance the speed, efficiency, and accuracy of plant leaf disease detection system, making them more practical for real-world agricultural applications. Deep learning models trained on GPU tend to achieve higher accuracy in disease detection. GPU allow you to experiment with larger and more complex models, which can capture subtle disease-related patterns in leaf images. Plant leaf disease detection often involves training on large datasets. GPU and CUDA manages to handle large datasets without running into memory constraints.

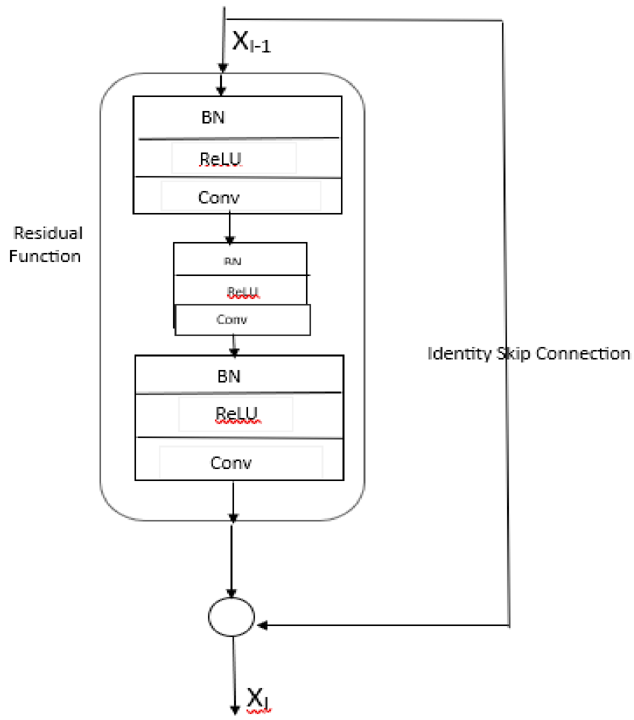

Figure 5. ResNet Model for detection

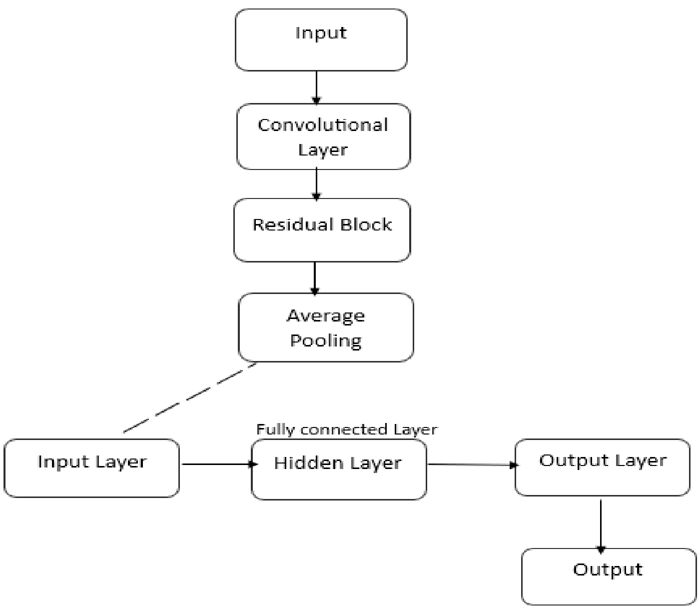

Figure 6. ResNet Layers in Disease Classification

Input: This is where your input data is fed into the network.

Convolutional and Pooling Layer: Before the residual blocks, there are often several convolutional layers followed by pooling layers. These layers are responsible for learning hierarchical features from the input data.

Residual Blocks: The core of the ResNet architecture consists of multiple residual blocks. Each residual block contains the following sub-components:

- Convolutional Layer with ReLU activation
- Another Convolutional Layer with ReLU activation
- Shortcut Connection: This is an omitted link which directly includes the data block to the outcome of the second convolutional layer. This shortcut helps in avoiding the vanishing gradient problem.

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These residual blocks can be stacked together, and the number of residual blocks can vary depending on the specific ResNet variant (e.g., ResNet-18, ResNet-50, etc.).

Pooling Layer: After the stack of residual blocks, a pooling layer is often applied which diminish the geometric properties of the attributes. This layer computes average value of each feature map, which results in providing an individual data point.

Fully Connected Layers: Following the pooling layer, there are usually one or more fully connected layers with ReLU activations. These layers help in learning complex patterns from the features extracted earlier.

Output: The final output layer depends on the specific task you are working on. For example:

- For image classification, you might have a soft max activation layer with as many units as there are classes.
- For object detection, you might have multiple output layers, including bounding box regression and class prediction layers.

The exact number of convolutional layers, residual blocks, and fully connected layers can vary depending on the ResNet variant and the specific application. ResNet variants differ in terms of depth, with deeper networks having more layers and typically achieving better performance on certain tasks at the cost of increased computational complexity.

$$G(y)=F(y)+y \text{ ------(1)}$$

In equation (1) let y denote the initial inputs to the first layer, and G(y) denote the target mapping function that transforms y into the output of the stacked layers. In the process of training the model, the task of acquiring the desired mapping function G(y) can be redefined as the task of learning the residual mapping function F(y). This can be expressed as F(y) = G(y) - y, with a specific reference to the inputs y for each layer. Considering that the original mapping function becomes F(y) + y, the weights associated with the stacked layers responsible for F(y) can be set to zero. This adjustment simulates a "shortcut connection" between the layers. The model is represented in Figure 7.

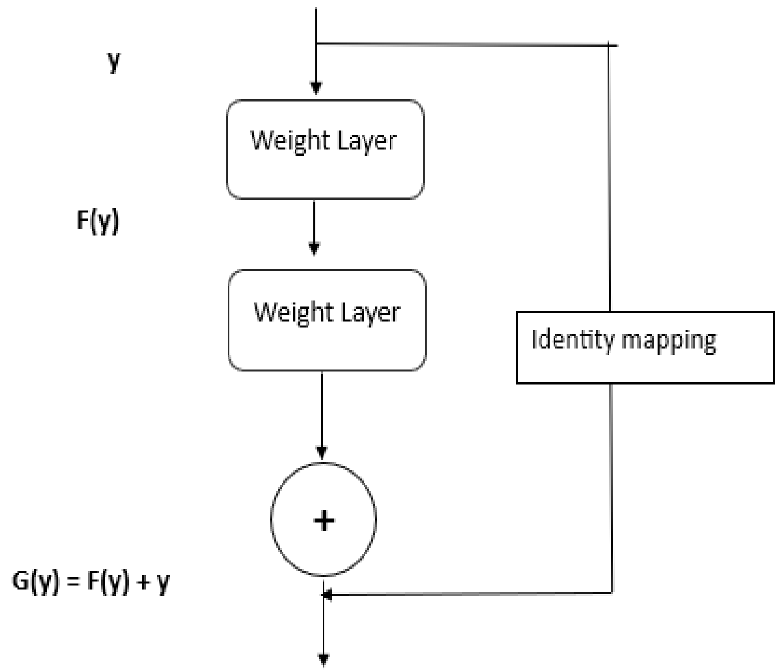

Figure 7. Equation for Identity Mapping

2.5 Evaluating And Testing the model for disease identification:

Epochs is one complete iteration where the entire training data set undergo the training process. There are mainly classified as 3 phase epochs early, mid and late phase epoch. At every epoch the model parameters like weights, layers of neural networks are updated.

Run the epochs in the implementation and then test for accuracy of the ResNet model.

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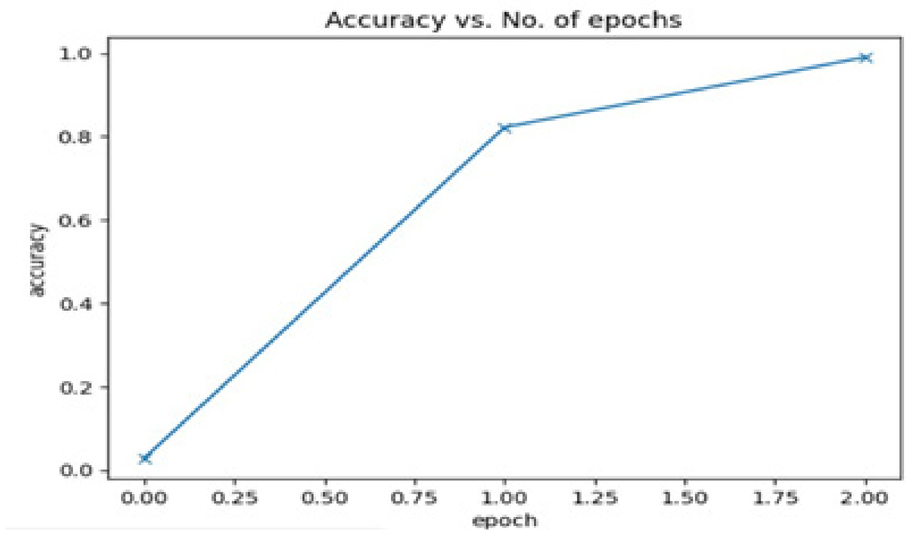

Figure 8. Accuracy for ResNet

accuracy = (correct_predictions / total_samples) * 100

The maximum accuracy recorded for this model after running all the epochs of model is 0,992 which is equivalent to 99,2 %.

RESULTS

We employed 2 machine learning algorithms one for object detection and another for plant leaf disease detection. Every algorithm in machine learning has an accuracy rate. For detecting the leaves present in an image we used R CNN which is having mean average precision as 54 %. After object detection we get an extract a single leaf from the images and label it for the next process of disease identification in below shown figure 9.

The second major step in this is process is application of ResNet and identifying the disease. We implemented ResNet and trained the model to get analysis on the data provided. Some parameters which are important to accurate prediction of training data are analysed in the model. They are learning rate for a batch, validation loss for an epochs, and accuracy for each epoch.

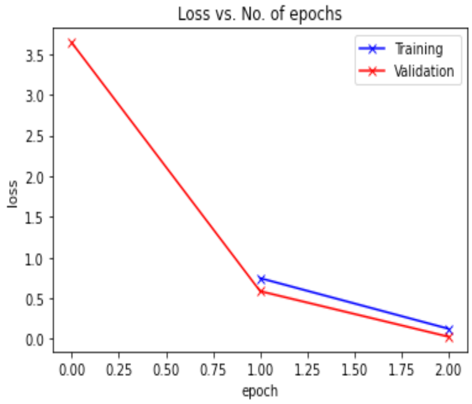

Figure 10. Validation loss

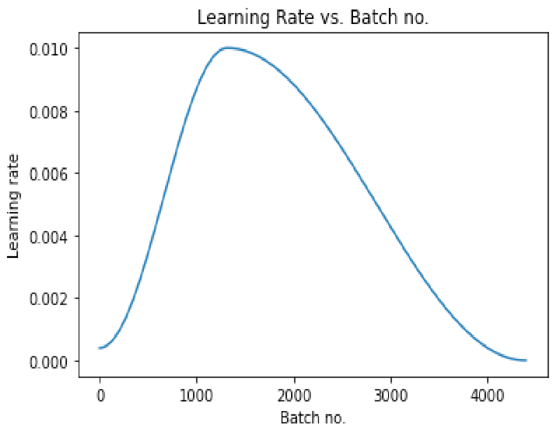

Figure 11. Learning Rate

Validation loss which is represented in figure 10 is calculated for training and evaluating the neural networks which describes about how well a model is about to perform on the new or unseen data set given. From validation loss graph we can estimate the status of overfitting in the model. When the training loss is decreasing then the validation loss in creases which is the best example of overfitting model. Overfitting occurs when a model performance is too poor in training the unseen data. Based on validation loss graph we can optimize the loss function. Our ResNet-9 has a suitable validation loss so no need to optimize the loss function further.

From figure 11 we get Learning rate which describes over time is used to measure the step size at which the prototype components were enhanced using training data. We have warm up schedule which starts with minimum learning rate and increases gradually for certain number of epochs.

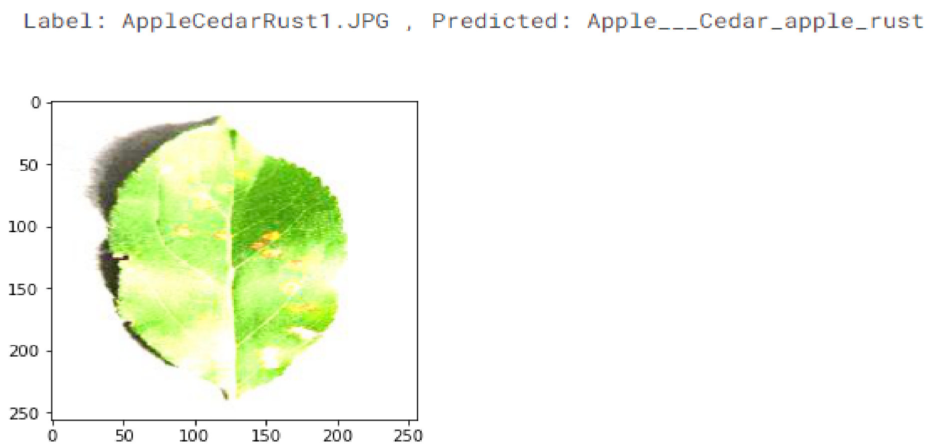

Figure 12. Apple Rust leaf

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In the testing stage of the model when we input a leaf image in the model it gives the disease name. For the above apple leaf, it is detected as apple rust. Finally, after training the model, we got an accuracy rate of 99,2 %. It means it can detect the leaf disease correctly for 99,2 % cases.

DISCUSSION

Our current implementation detects the diseases attacked to crops in the field. But this implementation is limited to machine learning only. We wanted these results should be accessible to farmer at time to time easily through their mobile devices. So, we wanted to develop a mobile application or a communication channel bots like telegram bot to detect the plant leaf diseases easily through their mobile phones. We wanted to connect our implementation to a telegram bot through an API so that the farmer can take the crop photo and upload in the bot. The bot thus analyse the images provided by the farmer and tells the farmer about the kind of disease it gets attacked. So when farmer upload the photos regularly to the bot he can monitor it time to time and can detect the crop diseases at early stage. Based on the disease he can use the customized fertilizers and pesticides to remove the disease and can prevent the crop failure at an early stage.

Some of the literature surveys we have done to know the existing work in this topic.

In article[1] majorly described many strategies for providing our farmers with up-to-date knowledge and insights using cloud computing. Unquestionably, the primary means of obtaining food and ensuring the survival of life on this planet is agriculture. It is anticipated that our farmers' activity in the agricultural land parcels would undergo a number of modifications. Intelligence representation technologies and the expanding selection of Smartphone applications will soon bring about a number of changes in farmers' daily life. Datasets from historical production, land use, and local climate conditions are utilised to compare analyses. The advantages for businesses and educational institutions embracing cloud computing services are cost savings, scalability, time shifting, increased fault tolerance, and ease of use. Three crucial components: a strong ecosystem, virtualization, and network intelligence. The farmer will be able to quadruple their produce and triple their income thanks to this e-learning. Through the online discussion forum, farmers can also share their struggles and experiences. This may serve as motivation for beginning and untrained farmers.

dCrop in this research [2] gives farmers access to a smartphone app that can be used to anticipate crop diseases by taking use of the high Smartphone camera sensors and processing power. This is the newest development in intelligent agriculture. This study employs deep learning techniques and computer vision technology to aid in the prediction of agricultural diseases. On a publicly available dataset of 54,306 pictures, including both sick and healthy plant leaves, a deep convolutional neural network (DNN) is trained. The train set is familiar in training the architecture, and split the information skilled for validation is used. The trained model can recognise 14 crop species and 26 illnesses with an accuracy of 99,24 %. As a tangible output of this research, dCrop, a smartphone application created utilising the trained illness prediction model, is made available. The farmer can use the app to record crop photos and examine them for the presence or absence of illnesses, displaying the of the proffered solution.

There are two goals addressed. Initially a mobile app-based approach that displays the most recent sensor readings and effectively enables field administration from a distance is shown. Secondly, a prototype surveillance system built on the Internet of Things is suggested, and it incorporates the idea of various categorization utilizing Machine & Deep Learning using tags to manifest farms. In order to achieve this, SVM & CNN were compared, and the best model was selected using the accuracy index. A proper use of natural and other resources is ensured by the integration of IOT into agriculture tracking system, which makes it simple and effective for tracking farm conditions and take required action. Various animal categorization prototype and an app-based agriculture tracking system were the two goals that were effectively attained by this work.[3]

In order to produce an effective outcome, this article [4] proposes a vital survey of several techniques including crop choice, planting, invasive identification, and tracking the system. The study combined picture handling, ML, IOT, & use of AI to focus on the complete system. AI, DL, The multi-sensor integration technique, & Embedded hardware can everything be utilized to invent Smart Robots. intelligent robot should be capable of weed detection and removal, sensing the amount of chemicals required, seed sowing, sensing humidity, providing information to smartphones, & locating fields. Robot can also be trained using neural network techniques using all the data. Additionally, current interest in automating weed sprayers and pest and weed identification led researchers to draw the summation that integrating computer vision methodology in fields to lowers burden.

In the current article [5], we outline a new IoT-enabled IA framework for facilitating secure data sharing among its many organizations. We do this by utilizing deep learning and smart contracts. To provide safe data transfer in IoT-enabled IA, we first create a novel authentication and key management method. A revolutionary deep learning architecture is then employed by the CS to analyse and further detect intrusions using the encrypted transactions. To solve complicated agricultural challenges like yield prediction, water feed calculation, and

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other similar ones, huge and real-time data are generated, analysed, and transferred to the cloud server (CS) in a typical intelligent agriculture (IA) ecosystem. This enables farmers and other involved parties to make wise decisions that raise agricultural output and product quality Data exchange, monitoring, and storage are all made more difficult by the distributed nature of IA entities and the use of unencrypted wireless communication.

The context of this work [6] is the WSN blueprint that uses inexpensive, low energy solar sensor points collect information on soil characteristics & environmental conditions is presented. The soil moisture sensors are the most crucial of all the installed sensors because of several problems with price, setup, dependability, and calibrating. So, utilizing specific information collected by various sensor mounted to point, this paper offers DL technique grounded on LSTM networks which produce a digital earth wetness sensor. The effectiveness of suggested soft sensing approach has been validated in this research by execution calculation of the digital sensors & a thorough contrast with alternative education centered method.

We create a new [7] IDS grounded on deep learning foreseen for the boundary SA in harsh nature. To identify attacks at the network's edge, a hybrid technique is built by fusing a two-way gated recurrent unit, LSTM, and multinomial logistic classifier. The suggested IDS handles lengthy sequences of network data using the TBPTT method to enable faster learning. In addition, we offer a deployment framework for recommended IDS in harsh nature of SA along with an attack scenario. Extensive tests utilising CIC-IDS2018, ToN-IoT & Edge-IIoTset datasets, three publicly accessible datasets, demonstrate the efficiency of introduced IDS over various old & modern approaches.

This article[8] discusses big data applications that are ideal for precision agriculture, as well as ways for creating data, availability of innovation, availability of equipment, & availability of software equipment and information methodologies. By means of the access of ICT in smart farming, which generates latest architecture for increasing production, renewable farmer increment in substantial answer including rapid democratic growth.

The primary aim of this research[9] is to examine the benefits of utilizing DL to field methodologies. This works cited examines the possibility for employing techniques from deep learning for sorting or estimate in precision agriculture in fields of agriculture connected to info examination & picture examination. DL algorithms are differentiated by neural networks primarily by their extent, which also gives them the ability to find latent patterns in unlabeled, unorganised information. Deep learning networks have a huge advantage over earlier algorithms since they can do automatic feature extraction without the need for human interaction.

Rooted on date fruit development stage,[10] we designed a IHDS. The suggested decision approach identified the 7 various maturation grade of date fruit with the help of computer vision & DL methodologies. We created six alternative DL systems in the IHDS, and each one yielded a different level of accuracy with regard to development levels indicated earlier. Info collection gathered by the Centre for Smart Robotics Research were utilized by the IHDS. The proposed IHDS's maximum performance metrics were 99,4 %, 99,4 %, 99,7 %, and 99,7 %, respectively.

The utility of models based on deep learning (AlexNet, VGG-Net, and ResNet) in practical texture classification issues, such as recognising plant diseases tasks, is examined in this study.[11] The models were trained on object categories (ImageNet). A machine-learning classifier receives texture features that have been taken from several layers of pre-trained Convolutional Neural Network models. RGB textured images from publicly accessible datasets and datasets with pictures of healthy and unhealthy plant leaves from various species were utilised for the experimental evaluation. We contrasted our methodology with feature vectors produced by conventional, manually-crafted feature extraction descriptors calculated for the same photos and end-to-end deep-learning algorithms. The recommended method exceeds convention & end-to-end CNN methods with regards to processing speeds & discriminative power, and additionally provides a answer regarding the matter of specific info collection accessible for precision agriculture.

To facilitate pest recognition, AI & picture identification approach are integrated with devices in the environment and IoT.On basis of smart infestation recognition [12] & nature IOT Information, day to day farming methods & infestation recognition system on mobile applications are analysed. We utilised deep learning and the most advanced AIoT technologies to smart agriculture. To locate Tessaratoma,papillosa & analyse natural data collected by nature stations by LSTM to anticipate the occasion of

infestation, we employed DL YOLOv3 for picture identification. The findings of the trial indicated that 90 % of pests could be correctly identified. The use of less pesticides and lessening of soil injury from pesticides can both be accomplished by precise positioning.

In this study [13], a differentiation among grains vigour identification & estimate was recommended using the spectral and image data of multispectral pictureing. CNN & hyperspectral imaging technology were assessed for their capacity to recognise and forecast maize seed vitality. Four seeds with different levels of vigour had their hyperspectral data (10 hours before to germination; 144 samples each) collected. In order to compare the impacts complex scattering rectification & PCA, the spectral information set was modelled using SVM, an ELM, 1DCNN. On the original spectral data, 1DCNN performed best, with an accuracy recognition rate of 90,11 %.

We undertake SLR & provide thorough analysis of research [14] using publicly accessible datasets and data gathering methods. Numerous crops have been studied primarily using hyperspectral images and vision-centered techniques, containing grapes, paddy, apples, cucumbers, maize, tomatoes, wheat, and potatoes. In comparison to conventional classifiers, SVM & LR sorts showed improved speed in trials. These methods portray illness localisation as a bottleneck to disease identification in addition to picture taxonomy. There is a growing trend in cognitive CNNs that have transfer learning and attention mechanisms. Although bulk employ accuracy, recall, precision, F1 Score, & confusion matrix, there is no universally accepted performance measurement method.

Considering DL methods, the research [15] gives UAV categorization at MMW radar. Radar systems with mmWave technology provide improved resolution and help detect tiny drones. Convolution neural networks (CNNs) are used in existing drone classification to accomplish drone categorization after converting the RCS signature into images. Every signature conversion results in an additional computational burden; a CNN model is subsequently trained with a set learning rate. As a result, the accuracy of drone categorization using CNN in a highly dynamic environment is poor. By incorporating a weight optimisation model that prevents the gradient from flowing through the LSTM model's hidden states, this study presents an enhanced long short-term memory (LSTM). Additional ALRO model for LSTM model training. The results of the examination demonstrate that LSTM-ALRO outperforms the current CNN-based drone classification model by achieving substantially higher drone recognizes with the accuracy of 99,88 %.

Agricultural robotics, forecasting analytics, & earth & field observation are the 3 important places spot AI begins to appear. In this paper [16], farmers are utilising sensors and soil sample more often to collect data that farm management systems can utilise for additional research and analysis. Through an overview of AI applications in the agriculture industry, this article makes a contribution to the area. The article begins with context of AI and a conversation including various AI techniques used in cultivation sector, including ML, the Internet of Things & computer vision. These techniques are used to collect data applying sensors & visualizing systems for farming & watering seepage. Additionally, it has been demonstrated that using AI algorithms increases excellence,efficiency, & durability are preserved. At last, the advantages and difficulties of AI algorithm and compare and contrast several AI approaches used in precision agriculture, including ML & picture manipulation.

Growing population, globally climatic change, and rising food demands have all contributed to an increase in agricultural output in the Big Data era, which is fuelled by plant phenotyping. For molecular plant breeding to boost crop output,efficient characterization of sorghum traits at the level of the individual plants and organs is essential.Accuracy, clarity, & quick measures are produced by LiDAR (light detection and ranging) sensors. For the specific purpose of segmenting sorghum plants, research used four 3D point cloud-based DL algorithms, namely PointNet, PointNet++, PointCNN, & dynamic graph CNN. The segmentation findings were then used to extract phenotypic features. With a mean segmentation accuracy of 91,5 %, PointNet++ excelled the remaining 3 DL algorithms & delivered the optimal segmentation resultis proposed here.[17]

This research [18] first examines current IoT technologies are utilized in Smart Sustainable Agriculture (SSA) to identify architectural elements that could make the creation of SSA platforms easier. The current state of SSA research and development is examined in this study, along with the existing information landscape, and a framework based on the IoT & AI is suggested as a place to start for SSA.

One of the main problems in urban cities is traffic congestion.[19] The standard techniques that are normally used to control traffic using various sensors are fewer accurate & more costly. DL approaches are used in intelligent solutions show promise in terms of increased efficacy, quick decision-making, and cost efficiency. This article tries to offer a quick, more precise, and more affordable solution to the traffic control problems, particularly at the traffic signals. For recognising vehicles, classification, and counting, 3 DNN system—Faster R-CNN, Mask R-CNN, and ResNet-50—are constructed & evaluated. 3200 photos of various motorcycles make up the set of images needed to train the models. The NVIDIA 1060TI 3GB GPU is put to use for training.

One of the finest methods for object detection in the R-CNN depends upon DL is the Faster R-CNN (R stands for "Region"), where it combines the RPN framework & Fast R-CNN framework. The ROI Pooling layer, a network for CNN secure end-to-end item identification, is directly related to the proposal obtained by RPN. Depending upon the execution of Faster R-CNN in the VGG16 network, it is discussed whether the ResNet101 network and the PVANET network can implement the faster R-CNN. Caffe's deep learning framework can be used to train a variety of faster R-CNN models. Using mean average precision (mAP) as a measurement metric, the experimental outcomes may be compared to determine which model is more accurate. The numerical findings demonstrate[20] that the PVANET network developed faster R-CNN.

Employing the data sets of healthy leavesin this research [21], apple healthy leaves, black star disease, cedar rust disease, & apple grey-spot disease to examine the recognition & categorizing of apple leaf illnesses.SVM picture section classifier, ResNet, & VGG CNN approach was utilized to compare & enhancement. where the ResNet-18 containing less levels of ResNet achieved a 98,5 % accuracy rate, producing stronger recognition results.

Computer techniques[22] were inspired by plant diagnosis, which traditionally relied on expensive and time-consuming professional visual inspection or, where necessary, biological studies. To identify plant diseases from leaf photos, these techniques employ deep learning, notably convolutional neural networks like "ResNet." They attain great accuracy by utilizing an enriched dataset with isolated leaves on homogeneous backgrounds.

For the safety and security of food, crop disease identification[23] is essential, yet it is frequently difficult due to inadequate infrastructure. The demand for automated disease identification in agriculture has increased as a result of the development of digital cameras and computer vision technology. A ResNet34 model distinguished diseases with an astonishing 99,40 % accuracy using a dataset of 15,200 cropped leaf pictures. This exemplifies the promise of automated networks for the global detection of large-scale crop diseases.

The suggested method[24] proposes a characteristic extraction approach including differentiation of wealthy and diseased plants. In order to train the model, a deep convolutional neural network and knowledge sharing strategy are utilized. Various CNN models, like VGG16, VGG19, and AlexNet, ResNet-34, ResNet-101, ResNet-50, and ResNet-18 are employed in to get better outcomes.

Primary picture manipulation and deep learning techniques, like picture reversing, cropping, revolution, hue alteration, PCA hue augmentation, disturbance addition, Generative Adversarial Networks, and Neural Style Transfer (NST) methods, were used to create the enhanced plant leaf disease datasets. Modern transfer learning methods, such as VGG16, ResNet, and InceptionV3, were utilized to examine how well the data augmentation strategies performed.[25,26,27]

CONCLUSIONS

We've examined a sizable dataset made up of pictures taken by drones in diverse field settings. This extensive dataset underwent rigorous processing using advanced Machine Learning techniques, Consisting of Regional Convolutional Neural Networks(CNN) and ResNet. We conducted detailed testing after receiving intensive instruction to spot early indications of leaf diseases. Our findings were truly remarkable, as the ResNet model demonstrated exceptional performance by delivering an outstanding accuracy rate of 99,2 %. significance of our method in the early detection and management of leaf diseases is highlighted by this amazing accuracy, which holds great promise for agricultural practices.

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