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An Overview of Computer Vision Techniques in Agricultural Disease Management

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Abstract - *Conditions drop the productivity of factory. Which circumscribe the growth of factory and quality and volume of factory also reduces. Image processing is stylish way for detecting and opinion the conditions. In which originally the infected region is set up also different features are uprooted similar as color, texture and shape. Eventually, bracket fashion is used for detecting the conditions. This paper has been divided into three main corridors. In the first part, a comprehensive review grounded on algorithms is handed were the major algorithms and workshop conducted using image processing and artificial intelligence algorithms have been compared. The alternate part discusses the fabrics and compared the former workshop. also, a comprehensive discussion grounded on the delicacy of the results was handed. Grounded on the review conducted, a detailed explanation of the ails discovery and bracket performance is handed. Eventually, the findings and challenges in factory splint discovery using image processing are epitomized and bandied.*

Key Words: **Neural Networks, CNN, Image Processing, Bracket, Flask.**

1.INTRODUCTION

India is primarily an agrarian country, with husbandry employing the maturity of its people. Over 65 of the population is employed in husbandry, making the country an agrarian nation. [3] husbandry exploration aims to increase productivity and food quality while reducing costs and adding gains. The agrarian product system is the result of a complex commerce between soil, seeds, and agrochemicals. Vegetables and fruits are the most precious agrarian products. An explanation of pests and factory conditions Factory conditions and pests are among the types of natural disasters that can stymie a factory's normal growth and indeed affect in factory death throughout the factory's entire life cycle, from seed development to seedling growth.[4] To gain more precious products, a product quality control is principally needed.[2] The use of ML and DL in factory complaint discovery has gained fissionability and shown promising results in directly relating factory conditions from digital images. Traditional ML ways, similar as point birth and bracket, have been extensively used in the field of factory complaint discovery. These styles excerpt features from images, similar as color, texture, and shape, to train a classifier that can separate between healthy and diseased shops. These styles have been extensively used for the discovery of conditions similar as splint blotch, fine mildew, and rust, as well as complaint symptoms from abiotic stresses similar as failure and nutrient insufficiency but have limitations in directly relating subtle symptoms of conditions and early- stage complaint discovery. [5] These ways have demonstrated the capability to directly identify and classify factory conditions. Limitations and difficulties still live and must be resolved. To produce generalizable models and increase the number of intimately available datasets for training and assessment, further exploration is demanded. This review summarizes the current state of exploration in this area and provides a thorough understanding of the advantages and disadvantages of machine literacy and deep literacy ways for factory complaint discovery. Its novelty stems from the breadth of content of exploration published from 2015 to 2022, which explores colorful ML and DL ways while agitating their advantages, limitations, and implicit results to overcome perpetration challenges. In summary, the field of factory complaint discovery using ML and DL ways is a fast- moving target with encouraging issues. The composition is a useful tool for factory complaint discovery experimenters, interpreters, and assiduity professionals who want a deep understanding of the content because it provides perceptive information about the state of the field's current exploration. The benefactions made by this exploration composition are listed in the section that follows:

• This paper gives a summary of recent advancements in the use of ML and DL ways for factory complaint discovery. It offers a thorough grasp of the slice- edge styles and procedures applied in this field by encompassing exploration published between 2015 and 2022.

• This review looks at a variety of ML and DL ways, similar as CNNs, DBNs, image processing, and point birth, for relating factory conditions. It also discusses the advantages and disadvantages of these ways, including data availability, imaging quality, and the capability to distinguish between healthy and diseased shops. The composition demonstrates how the operation of ML and DL ways greatly improves factory complaint discovery speed and perfection.

• A number of factory complaint discovery datasets, similar as Plant Village, the rice splint complaint dataset, and datasets for insects that affect soybeans, sludge, and rice, have been examined in the literature.

• The study covered a number of performance evaluation criteria, similar as accurate recall angles, bones similarity measure (DSC), and crossroad of unions (IoU), that are used to gauge how accurate factory complaint discovery models are. There are seven primary sections in the composition. In Section 1, a brief summary of factory complaint and pest discovery and its significance is given. Section 2 discusses the difficulties and problems associated with detecting pests and factory conditions. Section 3 presents the deep literacy approaches to image recognition and their operations in factory complaint and pest discovery. In Section 4, a comparison of popular datasets and the performance criteria of deep literacy ways on colorful datasets are handed. In Section 5, the problems with the current systems are listed. Section 6 presents the discussion regarding the identification of pests and factory conditions. In Section 7, the exploration work's conclusion and implicit unborn exploration directions are covered. [5] A presto, automated, and accurate system of complaint discovery is demanded.

Fig -1: Infected leaf of cotton plant

2.PLANT DISEASE AND PEST DETECTION: CHALLENGES AND ISSUES

In the field of factory complaint, artificial intelligence (AI) technologies have lately been used to identify infestations and abnormalities in shops. These technologies have the power to revise the styles used to descry, diagnose, and treat factory conditions. We'll examine the numerous artificial intelligence (AI) technologies that have been put forth for detecting abnormalities and infestations in shops, as well as their benefits and downsides, and how these technologies are affecting the field of factory pathology, in this passage. Machine literacy (ML) is one of the most popular artificial intelligent (AI) technologies in factory pathology. ML algorithms, like the c 4.5 classifier, tree bagger, and direct support vector machines, have been used to classify factory conditions from digital images. These algorithms can be trained to identify particular patterns and symptoms of conditions, which makes them applicable for grading ails when they're in their early stages.

Fig -2: Viral complaint on splint [9]

A significant quantum of annotated data is needed for ML algorithms to serve duly during training, so they might not be applicable for conditions that have no way been observed ahead. also, DL technologies have been proposed for the identification of infestations and abnormalities in shops, similar as CNNs and DBNs. When it comes to the identification and discovery of lesions from digital images, these technologies have demonstrated encouraging results. [6][7] DL models are suitable to fete subtle complaint symptoms that conventional image processing ways might miss by automatically learning features from the images. still, Deep Learning models bear a large quantum of labeled training data and high computational outflow, which could be a debit for some operations. Computer vision (CV) is another AI technology that has been used in factory pathology. Certain regions of interest in images, similar as factory leaves and complaint symptoms, can be honored and localized using CV algorithms like object discovery and semantic segmentation. [8] These algorithms can automatically convert the images into identifiable patterns or features, which can also be combined with ML or DL algorithms to descry and classify conditions. still, for model training, CV algorithms bear a large quantum of labeled image data, and they might not be applicable for conditions that have no way been observed ahead. Each of the four images in Figure 1 represents a distinct stage in the discovery of factory conditions. The results of the complaint identification are shown in the following image, which is the input image in the first case. The factory lesion's segmentation results are shown in the final image, while lesion discovery is featured in the third image. Artificial intelligence (AI) technologies have demonstrated encouraging issues in the identification of anomalies and infestations in shops.

2.1 Analysis Of Standard Styles For Detecting Pests And Factory Conditions

These styles have shown great pledge for adding crop yield, relating factory lesions, and optimizing factory growth. In comparison to traditional approaches, ML and DL- grounded styles give traditional approaches, ML and DL- grounded styles give several benefits and have the eventuality to revise husbandry. Traditional approaches to husbandry and

botanical studies calculate heavily on homemade examination and expert knowledge.

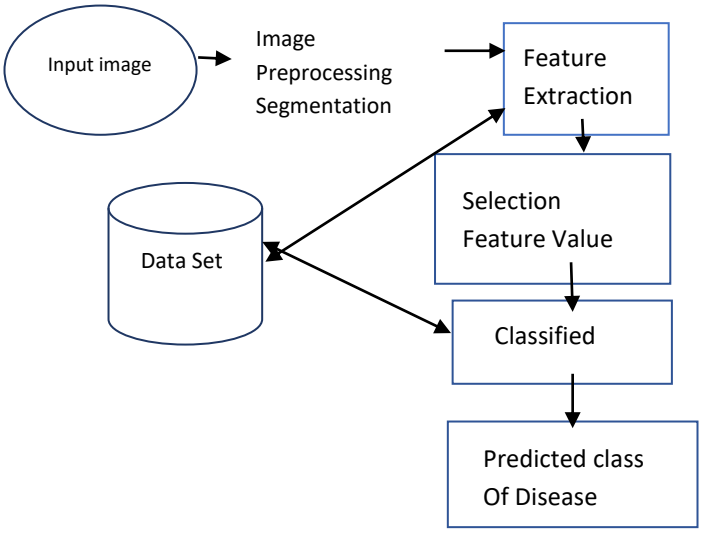


Chart -1: Basic image recovering way for detecting factory conditions. [19}

These styles are frequently time- consuming, physically demanding, and prone to mortal error. In discrepancy, ML and DL- grounded approaches can automate these tasks, reducing the need for mortal intervention while adding process perfection large quantities of data, similar as images, detector data, and rainfall data, have been anatomized using ML and DL approaches to identify patterns and make prognostications. For illustration, ML algorithms similar as the c 4.5 classifier and tree bagger are used to prognosticate crop yields, identify factory lesions and pests, and optimize factory growth. [12] [13] [14] DL models, similar as CNNs and DBNs, have been applied in factory lesion identification grounded on image analysis and bracket, furnishing better delicacy and robustness than traditional image processing styles. [15][16][17] ML and DL- grounded approaches have several advantages over traditional styles in husbandry and botany. These styles can automate tasks, ameliorate delicacy and effectiveness, and assay massive quantities of data. Because these styles bear a large number of labeled features, they may not be applicable for preliminarily unknown lesions. further exploration is demanded to develop generalizable models that can be applied to colorful crop species and conditions, as well as to make further datasets available to the public for prophetic model training and confirmation for performance analysis.

Fig -3: Viral disease on the leaf [18]

Also are some common symptoms of fungal, bacterial, and viral factory flake conditions:

1) Bacterial complaint symptoms include small light green spots that come water- soaked. As shown in Figure 1, the lesions expand and ultimately come dry dead spots.

2) Symptoms of contagion- caused factory flake conditions are challenging to diagnose. Contagions produce no egregious symptoms and are constantly confused with nutrient scarcities and germicide injury.

Mosaic Virus, for illustration, is generally transmitted by insects like aphids, leafhoppers, whiteflies, and cucumber beetles. Viral complaint on flake Look for unheroic or green stripes or spots on the leafage, as depicted in Figure 2. The leaves may be wrinkled or coiled, and the growth may be suppressed. [19]

2.2 Deep Knowledge Approaches For Image Recognition:

Deep knowledge approaches have come to be as an instigative way of detecting factory injuries. These RNN- rested ways have proven effective in relating colorful factory injuries from images. [20] DL is an area of machine knowledge that's primarily used for image type, object discovery, and natural language processing. Deep knowledge (DL) is a neural network- rested algorithm for automatic point selection of data. It does not bear important artificial point engineering. It combines low- position features to produce abstract high- position features that are used to discover distributed features and attributes in sample data. It outperforms traditional styles for image recognition and target discovery in terms of delicacy and generality. [21] [22] [23]

- **IMAGE PROCESSING:**

Complaint discovery in factory leaves can be fulfilled using respectable, effective, and reliable image processing ways. Image processing has multitudinous operations in fields

similar as biology, husbandry, drug, engineering, and computing. Motorized image processing ways are critical for detecting and classifying factory conditions beforehand on, before they spread throughout crops. [24] Digital signal processing is a methodology for carrying quick and accurate results about factory flake conditions. It'll reduce numerous agrarian aspects while adding productivity by detecting applicable conditions. For complaint discovery, the image of an infected flake should be examined using a set of procedures. As illustrated in Figure 3, the input image should be pre-reused before its features are pulled rested on the dataset. The conditions should also be classified using classifier ways specific to the data set.

- **IMAGE ACQUISITION:**

Image accession is the process of acquiring images and converting them into the asked affair format. For this operation, an analog image is originally captured and also converted to a digital image for farther processing. [25]

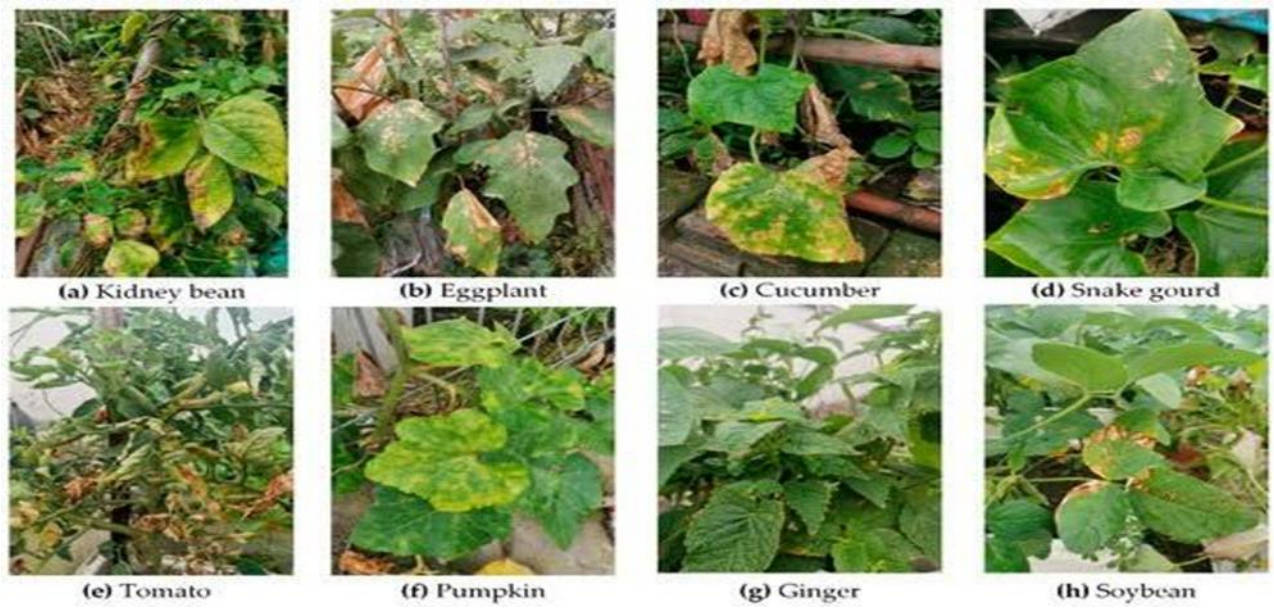


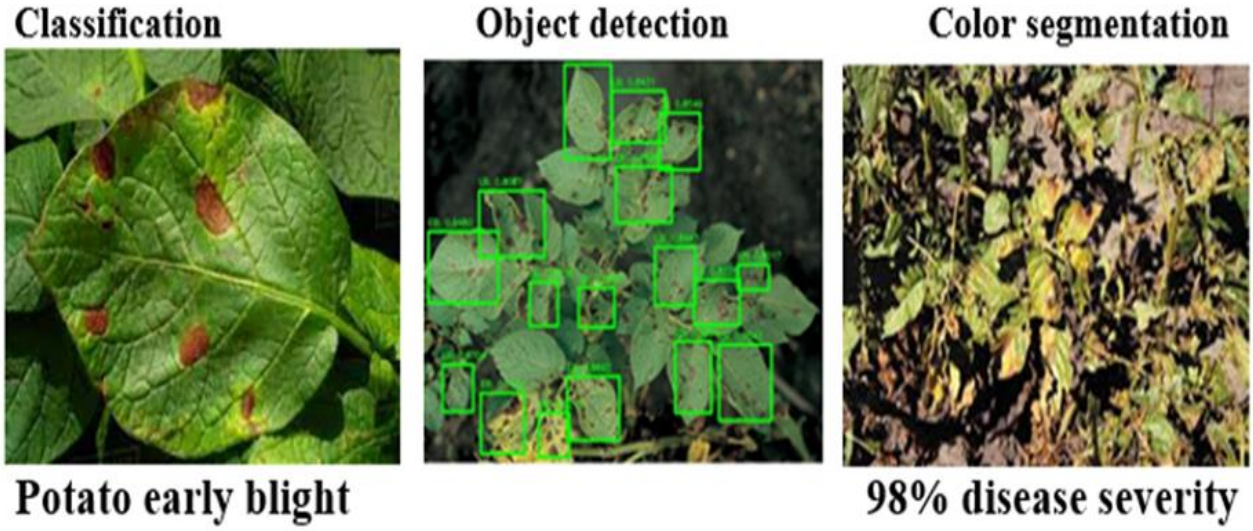
Fig -4: Leaf spot in eight common plants. These photos were taken in the greenhouse of Chengdu Academy of Agriculture and Forestry Sciences. [25], [26]

Preprocessing Segmentation contains process for image segmentation, image improvement and colour space conversion originally image digital image is enhanced by sludge. Leaf image is filtered form the background image. also filtered image's RGB colours are converted into colour space parameter. Hue Saturation Value (HSV) is a good system for colour perception. further image is segmented to a meaning full part which is easier to analysing. Any of the model rested, threshold rested, edge rested, Region rested and point rested segmentation has been done on the images. [25]

2.3 Convolutional Neural Network (CNN):

CNNs are a type of deep literacy model that's ideal for image bracket tasks similar as splint complaint discovery. The CNN armature is made up of multiple layers, including completely connected layers, maximum pooling layers, and normalization layers. [27] The first subcaste in a CNN is the input subcaste, while the alternate subcaste in utmost CNNs is convolutional layers, which prize features by applying colourful types of 2D pollutants to the image. As the number of images increases, dimensionally reduced pooling, also known as down slice layers, can be used to produce a further compact representation of the image. [28] Completely connected (FC) layers in a CNN are also known as learnable features, the uprooted features are reused in the FC subcaste for literacy and weights optimization. These layers are also responsible for making bracket which can be used to fete colourful factory conditions. The literacy process of CNN model begins with training, the input to the CNN are images along with their markers, after the successful training of the model, the model is suitable to identify complaint types. [29] The three main characteristics of the CNN are pooling, weight sharing, and position. The performance of process of CNN model begins with training, the input to the CNN are images along with their markers, after the successful training of the model, the model is suitable to identify complaint types.[30] The three main characteristics of the CNN are pooling, weight sharing, and position. The performance of process of CNN model begins with training, the input to the CNN are images along with their markers, after the successful training of the model, the model is suitable to identify complaint types. [30] The three main characteristics of the CNN are pooling, weight sharing, and position. The performance of speech recognition could be

enhanced by each of them. Greater adaptability against on-white noise is made possible by position in the complication bias's units, where certain bands are cleaner than others The decision- making process in a CNN for splint complaint discovery begins with the input of a splint image. The image is also reused through convolutional layers, where features are uprooted.



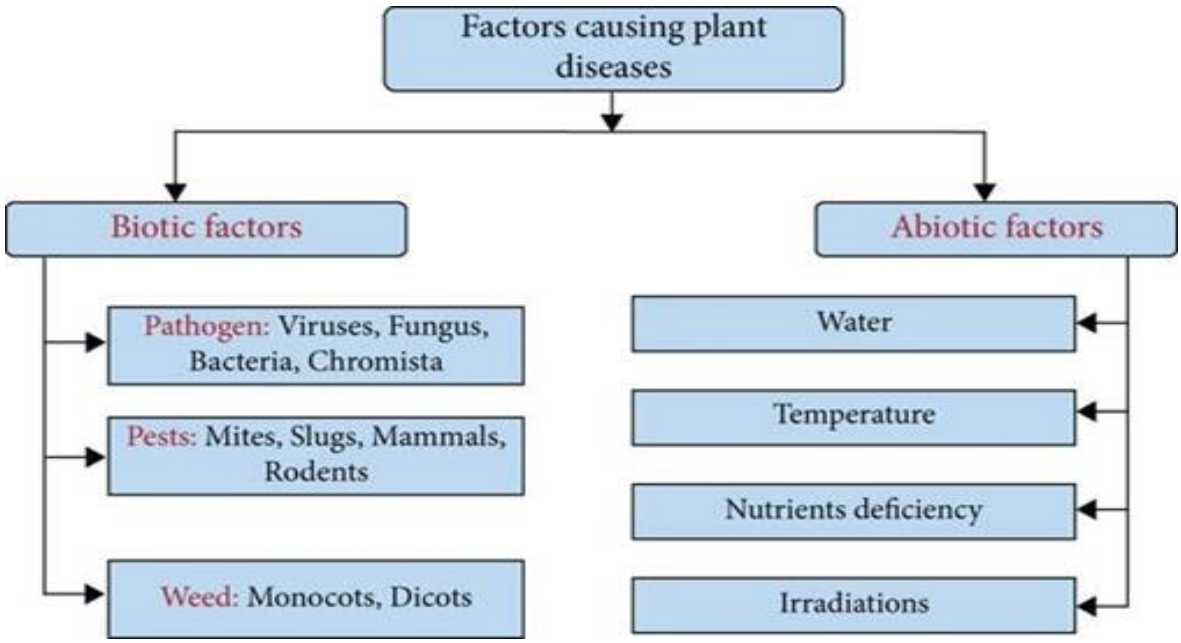
The performance of speech recognition could be enhanced by each of them. Greater adaptability against on-white noise is made possible by position in the complication bias's units, where certain bands are cleaner than others. The decision-making process in a CNN for splint complaint discovery begins with the input of a splint image. The image is also reused through convolutional layers, where features are uprooted. The performance of speech recognition could be enhanced by each of them. Greater adaptability against on-white noise is made possible by position in the complication bias's units, where certain bands are cleaner than others The decision- making process in a CNN for splint complaint discovery begins with the input of a splint image. The image is also reused through convolutional layers, where features are uprooted. The performance of speech recognition could be enhanced by each of them. Greater adaptability against on-white noise is made possible by position in the complication bias's units, where certain bands are cleaner than others The decision- making process in a CNN for splint complaint discovery begins with the input of a splint image. The image is also reused through convolutional layers, where features are uprooted. The model's affair is the probability that the splint is diseased or healthy. CNNs' armature of over- slice, down- slice, and learnable layers makes them ideal for detecting splint conditions. [31] The convolutional neural network (CNN) can be allowed of as a variation of the standard neural network. rather of using completely connected retired layers as described in the former section, the CNN introduces a special network structure that consists of interspersing so- called complication and pooling layers. An automatic system for classifying and detecting factory conditions from splint images was delved by exercising the.[32] Deep literacy approach. With the help of visual diagnostics, the developed model was suitable to identify 13 distinct conditions and descry the presence of healthy leaves. Each step of the process was covered in detail, starting with gathering the training and confirmation images and moving on to image preprocessing, addition, and deep CNN training and fine-tuning. [33]

2.4 Present State Of The Art

Still, advancements are needed as a result of reviews, new developments, and conversations. Crop product can be significantly increased encyclopedically through the use of technology. Former exploration has established the robustness of deep literacy (DL) and machine literacy (ML) ways similar as k- means clustering (KMC), naive Bayes (NB), feed-forward neural network (FFNN), support vector machine (SVM), k- nearest neighbor (KNN) classifier, fuzzy sense (FL), inheritable algorithm (GA) are included in this technology.

2.5 Factors Responsible For Plant Diseases:

Factors responsible for factory conditions Agrarian conditions may intrude factory growth and negatively impact crop product at different stages of development. [34]



(Repudiated) A methodical analysis of machine literacy and deep literacy-grounded approaches for factory splint complaint bracket a review [39]

Factory conditions can arise from colorful conditions during different stages of growth. [34] Crop complaint- causing variables are divided into two orders, according to [35] biotic factors and abiotic factors. [36] shops are impacted by biotic factors like contagions, fungi, bacteria, diminutives, and slugs, as well as abiotic factors like water, temperature, irradiation, and nutritive privation due to microbial infection harms factory growth. [37] The study included images of diseased factory leaves from the Plant Village dataset as well as healthy and diseased factory leaves from other datasets. [38]

A methodical analysis of machine literacy and deep literacy-grounded approaches for factory splint complaint bracket a review [39] and different images from other datasets showing healthy and diseased factory leaves have been epitomized in the workshop and consequently. also, the detail computer vision- grounded ways and proccsses including feld crops, image accession, splint image datasets, image preprocessing (test set, training set, and confirmation sets), data splitting, and performance assessment styles) for factory complaint discovery and classifcation have been easily indicated in the work. [39] Details about the factors that beget factory conditions have been depicted. Images of factory leaves with colorful conditions from the Plant Village dataset, as well as healthy and diseased leaves from other datasets, have been included. [40] Below are images of factory leaves with colorful conditions from the Plant Village dataset, as well as healthy images from other datasets.[41]

2.6 Plant Disease Identification And Classification:

DL, ML, and computer vision ways are critical to the husbandry diligence for the discovery and bracket of crop conditions. [42] In order to automatically identify and classify agrarian factory conditions, algorithms and styles grounded on prints of the plant leaf.

2.5 Ways For Classifying And Detecting Factory Conditions:

I. The NB Method erected upon the NB classifer conception, it's a probabilistic classifer variation. [43] It's assumed that the class markers have been assigned their posterior chances and that the previous chances of the patterns are known to live. Given this supposition, the data that belong to a specific class marker have their maximum liability values reckoned. keeping the posterior probability in mind. It's determined by multiplying the tentative probability of each point by the product, using Baye's theorem. Although this proposition generally fails in practical settings, it performs nicely well in numerous bracket problems.

II. The KNN Methodology It's a supervised, nonparametric machine learning fashion constantly used for pattern recognition [41]. It's grounded on the nearest neighbor rule, which is used to classify data in machine literacy operations. This fashion entails using the classifier to train the test pattern, after which it's distributed grounded on how analogous each training pattern is to the test pattern. The KNN classifier generates a value representing the class to which it belongs. Using the plurality vote of its neighbors, the object is assigned to the most popular class markers among its k- nearest neighbors. It performs the bracket process

using separate calculations and locally approached operations, much like a case grounded literacy model. [41]

DATA SET DISTRIBUTION	
Class Name	***No. of Samples***
Maize: Cercospora leaf spot disease	1025
Maize: Common rust disease	1220
Maize: Healthy Leaf	1120
Peach: Healthy Leaf	1050
Peach: Healthy Leaf	1273

Table -1: Distributing the Data Set

III. The Method of DT By dividing the data into several lower groups (tree structure) grounded on which division results in the lesser disproportion, the supervised bracket and retrogression algorithm in supervised literacy produces classifiers [41]. The entropy, or Gini indicator, is a generally used trait selection standard that's constantly used as a difference dimension. The system's eventuality to simplify result interpretation for humans is one of its advantages. A deep literacy tree might produce veritably little training error if it could have trained without being constrained by its depth. multitudinous variations of DT, similar as ID3, C 4.5, and CART, are considerably employed in different data mining and machine literacy operations. Using the SVM Method This supervised machine literacy classifier is defined by the separating hyperplane. The optimal hyperplane that maximizes the periphery between the data points of the two classes is set up using this fashion in high- dimensional space. SVM has a point called kernel tricks that are useful for nonlinear bracket. We look forward to carrying further distinct features in the high- dimensional point space. To finish it, the features can be converted using a variety of general functions, similar as the direct, polynomial, and radial base functions. Point metamorphosis may beget the confines of the point space to increase dramatically.

2.6 Deep learning (DL) techniques or algorithms:

The CNN Methodology CNN uses multidimensional data analysis through deep feed-forward neural networks. Once it classifies a specific highlight at some spatial positioning information, the CNN learns channels that are activated [44][39] The accuracy of various convolution filters with dimensions of 2×2 and 3×3 depends on the number of epochs used in their -

implementation. This depends on the dimensions of the filter. The CNN method can be used with a number of pre-trained architectures, such as VGG16, VGG19, ResNet50, ResNet152, InceptionV3, InceptionNet and DenseNet121. [45] The ANN Method Neural networks are models that The ANN Method Neural networks are models that replicate how biological systems, such as the brain, process information[48]. To create a network topology, Coefficients link artificial neurons, also known as processing elements (PEs). Experience is what identifies data links and patterns, not programming. Complex data can be interpreted and patterns can be found by using deep neural networks (ANNs). To build a network structure, connect artificial neurons, commonly referred to as processing elements (PEs). It is through experience, not programming, that data patterns and connections are found. ANNs are useful for extracting patterns from complex data because they can understand it.[46]

2.7 Gathering and Preparing Data Sets:

The RGB images that made up the data set included an equal amount of leaf samples that were infected and those that were not. To reduce the size of the data set, the images were compressed and split into five classes. To ensure optimal performance when used as input for the Convolution Neural Network Algorithm, the data set images must be processed after they are collected. To process the images, we employ Matplotlib and OpenCV. Map the alphanumeric class labels to a numeric label value using One Hot Encoder to encode the labels, which facilitates prediction. Next, images are rearranged to achieve a suitable data redistribution for the split process. In order to keep the machine learning model from overfitting, the images are split into training and validation sets. Images are then transformed into a 3D tensor in the form of (28,28,3) width = 28, height = 28, and channels = 3 (RGB) shaped arrays, ensuring that each image has the same parameters[47] Data set shows the sample images from the dataset, with representing healthy spots and representing bacterial spots. Four categories are healthy, Cercospora leaf spot, and the samples of northern leaf blight, common rust, and gray leaf spot shown in Data set. [48]

Fig -5: Cercospora leaf spot disease on Soyabean [51]

Fig -6: Common rust disease on Corn plant [49]

2.8 Applying The CNN Algorithm:

The specified input image is processed through the convolution step in order to extract features. That is how a CNN model starts. Take an example of an input image that functions as both a feature map and a feature indicator. Next, take the filter and apply each block of the filter to the input image that is being considered. Matrix multiplication is used to achieve this. Rectified Linear Unit, or ReLU layer, is a layer that operates as a progression to the convolution layer. Activation functions must be applied to feature maps in order to increase the non-linearity within the network. This is a result of how highly non-linear images are by nature. Negative values are removed from an activation map by setting them to zero. Max pooling involves dividing the input image into a collection of non-overlapping regions. This means that every region's output is its maximum value throughout all of them. Thus, with fewer parameters, we obtain a smaller image. Utilizing Tensorflow and Keras, we employed various packages to create Convolutional Neural Networks (CNNs).[50]

2.9 Saving The Trained Model:

It is advantageous to save the machine learning model along with all of its parameters after it has been trained. After it has been saved, we can load the previously trained model whenever necessary and perform classifications without having to start the model's training process over. The components of a Keras machine learning model are as follows: An architecture that describes the model's layers and their relationships is also referred to as a configuration. "State of the model" is a collection of weighted values, an optimizer (identified by putting the model together), A collection of metrics and losses that can be obtained by calling add_metric () or add_loss () or by compiling the model. Using the Keras API, all of these components can be saved to disk at once or only some of them can be saved selectively. For example, all of the components can be saved as a single archive in the TensorFlow Saved Model format (or the older Keras H5 format), and the architecture and configuration can be saved separately and usually as a JSON file.

3. CONCLUSIONS AND FUTURE WORK

The methods for identifying plant diseases through image processing have been reviewed and summarized in this paper. The four main methods for identifying plant diseases are SGDM, K-means clustering, SVM, and BPNN. These methods are employed to analyse the leaves of both healthy and sick plants. The impact of background data in the final image, technique optimization for "specific plant leaf diseases," and automation of the technique for ongoing automated monitoring of plant leaf diseases in real-world field conditions are a few of the challenges associated with these approaches [51] We have successfully developed methods for classifying diseases that are used to identify plant leaf diseases. It is possible to automatically detect and classify plant leaf diseases by using a deep learning model that has been developed. The thirteen species on which the suggested model is tested are tomato, strawberry, soybean, raspberry, potato, corn, pepper bell, peach, orange, grape, cherry, blueberry, and apple. With the help of this work, 38 plant classes were identified. Working with the Keras image data generator API was successful. This allowed us to perform image processing tasks. A sophisticated convolution model called the vgg-19 was also developed by us, and it was trained using data in order to make predictions. Our model produced a nearly accurate prediction. Our aim is to improve both the accuracy of the model and the android app, after we have effectively implemented these models.[52]

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