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Pest Detection in Plants Using Convolutional Neural Network

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Abstract: ***Agriculture or farming is an imperative occupation since the historical backdrop of humanity is kept up. Artificial Intelligence is leading to a revolution in the agricultural practices. This revolution has safeguarded the crops from being affected by distinct factors like climate changes, porosity of the soil, availability of water, etc. The other factors that affect agriculture includes the increase in population, changes in the economy, issues related to food security, etc. Artificial Intelligence finds a lot of applications in the agricultural sector also which includes crop monitoring, soil management, pest detection, weed management and a lot more. Significant problems for sustainable farming include detection of illness and healthy monitoring of plants. Therefore, plant disease must automatically be detected with higher precision by means of image processing technology at an early stage. It consists of image capturing, preprocessing images, image segmentation, extraction of features and disease classification. The digital image processing method is one of those strong techniques used far earlier than human eyes could see to identify the tough symptoms. Considering different climatic situations in various regions of the world that impact local weather conditions. These climate changes affect crop yield directly. There is a great demand for such a platform in the world of today which would enable the farmer market his farm products. We have proposed in this study a system where farmers can sell their products directly to customers without the intervention of distributors and traders. The predictive analytics system is necessary for the farmer to get the maximum yield which benefit the farmer. This may be done if the environment, market conditions and knowledge of the timely planning of farms are known properly.***

Keywords: Pest Detection, Artificial Intelligence, Agriculture, Image processing, Convolutional Neural Networks.

I. INTRODUCTION

India is an agricultural country, which depends on agriculture more than 50 percent of the people. The agri-business commitment to India's national revenue is all the more important, as farming in India is regarded to be a backbone in the Indian economy. Most Indians are dependent on agriculture explicitly or implicitly. Some are directly connected with agriculture and some others deal with these commodities [1]. India is able to produce food grains, which in the Indian economy may make a huge impact. In order to reach a desired Government mark, it is necessary to help small-scale farmers alongside the large farmers in the case of land, banking and other machinery. For over 58 percent of the population of India, agriculture is the major livelihood source. Gross Value in FY20, Rs. 19.48 lakh crore was expected to have been added to agriculture, forestry and fisheries (US$ 276.37 billion). At current prices, Indian share of farming and ally industries in the Indian Gross Value Added (GVA) amounted to 17.8% in FY20. In 2021, after the pandemic-led downturn, consumer expenditure in India is expected to return to its rise by up to 6.6 percent [1,2]. The Indian food sector is set to develop rapidly and annually, because of its great value-added potential, especially in the food processing industry, it is increasingly contributing to global food commerce. The sixth biggest in the world is Indian food and food markets, with retail sales accounting for 70%. 32 percent of the entire food market in India, one of the major sectors in India, is the Indian food manufacturing sector, rated fifth in terms of quality, accumulation, trade and anticipated growth. For April 2020 – January 2021, main exports of agricultural goods amounted to $32.12 billion. AI might provide an advantage for existing practices and procedures within the rural environment in order to achieve profitability and support. For example, dynamic capabilities such as AI may assist to identify changes in agricultural products' market value and explicitly offer planting and harvesting instructions to keep away from major crop losses. In general efficiency and sustainability, early disease detection and changed water system designs might enhance. Artificial intelligence-enabled weather forecasts constantly provide accurate, remarkable bits of knowledge in day-to-day farming. Such accurate data may help to reduce crop losses via preventive actions. With AI applications in farming groups, they can enhance the present strong IT capabilities after some time via learning. Because plant diseases may harm crops, they represent a significant danger to crop monitoring. Therefore, it is very important to diagnose and manage early plant illnesses. Often, this process requires the right diagnosis by a professional human competence. Specifically at distant areas and small farms in developing regions this knowledge is not always available. The creation of efficient image-based prediction techniques, including the use of smartphones, to capture high quality pictures, may help significantly to the initial diagnosis and decrease in waste.

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In the area of agricultural research, the rapid growth of deep learning technology has effectively implemented Convolutional Neural Networks (CNNs) that can overcome the disadvantages of machine learning. In the automated detection of pest conditions, the CNN model works well [3]. The CNN model comprises generally of two major operators, the convolutional stratum and the grouping stratum. The convolutional layer can extract more complicated and relevant picture characteristics automatically. The pooling layer lowers the amount of data parameters because of a high calculation of the convolution network. The subject of categorization of pest images on the basis of CNN models is mostly investigated in current research. However, it is more necessary to identify and locate every pest in the natural environment than to classify pests.

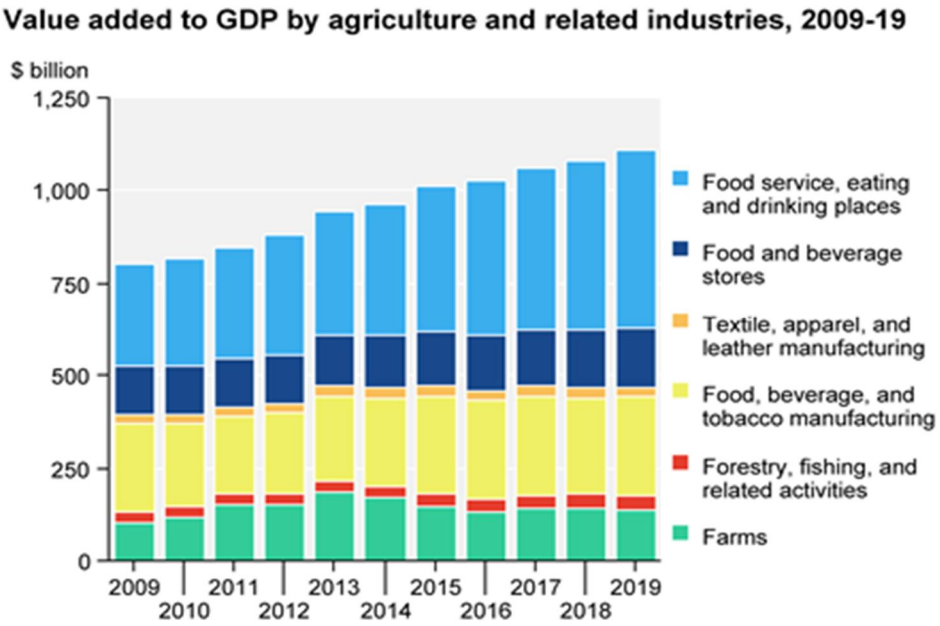

Figure 1: Farm Share of Agricultural GDP

Figure 1 shows the farm share of Agricultural GDP in India. The agricultural portion in GDP rose from 17.8% in 2019-20 in 2020-21 to 19.9%. However, GVA growth for farming continued to grow positive by 3.4% for the entire economy during 2020-21, while it contracts by 7.2% for the whole economy."

Previous yield forecasts were made by looking at the knowledge of the farmer on a given field and crop. However, given the quick changing conditions, farmers are compelled to grow more and more crops every day. As the existing state of affairs, many of them are not sufficiently informed of the new crops and of the benefits they obtain from their production. The productivity of agriculture may also be enhanced under a range of global circumstances via study and provision of crops performance [3,4]. The suggested system therefore takes the user's position as an input. The soil nutrients such as nitrogen, phosphorous and potassium are derived from the site, the predicted weather. Machine Learning and Multiple linear regression are used in the suggested system to detect the data pattern and process it under the input circumstances. In turn, this will offer the finest harvests possible under the conditions of the environment. The projection will be more accurate if last year's production is also taken into account. This method therefore proposes profitable crops for the farmer to choose directly.

There is a great demand for such a platform in the world of today which would enable the farmer market his farm products [4]. We introduced farmers and customers to this system for better and direct contact. The farmer is now transferring his goods to a certain agent, and he is asking the farmer to attend the market after a certain period to receive the cash from the sold commodity. At the expense of the market, the agent sells the goods to a different agency or dealer. Each agent attempts to remove his commission from it. There is no way for farmers to know how much their goods was sold and how much. There's no transparency. There is no facility for farmers to discover the product rates on various markets where they may sell their stuff for big profit. Farmers are often unaware of the government's initiatives and compensations. Despite all the possibilities offered by doors, the farmers cannot benefit from them. The major objective of this online application is to link consumers and farmers directly to farmers and consumers. Since the majority of farmers do not know about the latest equipment and technology owing to a job loss and time wasted [5]. If a farmer finds out about what pesticides or fertilisers he has used in his farm, his or her data will be kept so that they may readily find out what pesticides or fertiliser they have used to farm.

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II. LITERATURE REVIEW

The automatic detection of pests in recent years has been an important subject for study. In most situations, visibility, machine learning or technology for detecting herbs is picked and employed. However, in the same job there is typically no comparison of the many available approaches. Many computerized pesticide identification and recognition study focuses on a particular technical method, although many technological options are not being evaluated. In recent years, computer vision and identification of objects made enormous progress. Prior to this, the typical method was based on detectors' algorithms for features such as Salient Regions, SURF, SIFT, MSER, etc. Some learning methods using these attributes are employed when data is retrieved. Depends on specified functions, the performance of methods. Image classification is indeed a difficult procedure that must be redone if the issue and the dataset change [6,7]. This difficulty occurs in every effort to detect plant illnesses through the use of computer vision since they trust hand-made functions and algorithms for improved images. Deep learning techniques may be used to overcome the problem of manual extraction of features as feature extraction is done automatically. Machine and deep learning advances allow the reliability of item identification and detection to be dramatically improved. In the case of illness detection, machine learning approaches were used on the one hand. In agriculture research projects, several of these approaches were employed, such as Artificial Neural Networks (ANN's), Decision trees, K-means or KNN [7]. One of those technique proposed widely in the field of illness diagnosis is Vector Support Machines (SVMs). Various techniques have been analysed to identify diseases and classify them using machine learning in tomato crops. First, tomato yellow leaf curl disease is identified using RGB pictures and various master learning methods (SVM, linear kernel, quadratic kernel, radial base function, multilayer perceptron, multilayer kernel). The average accuracy of this method was 90%.

Bakhsh pour and Jafari (2018) developed a method for weed detection. Using an artificial neural network and a support vector machine, the pattern is identified for each species of plant. SVM has a 96.67 percent accuracy rating, whereas ANN has a 92 percent accuracy rating [8].

Ray et al. (2017) devised a method for detecting fungal illness at an early stage, and correctly diagnosing the disease aids in its prevention. It included an overview of current and upcoming disease detection techniques. On-field validation is aided using biosensors in this sector.

Carranza et al. presented a deep learning-based method for identifying species in herbarium collections. It focuses on how convolutional neural networks may aid with automated plant species identification. Image- In the convolution neural network method, net classification is highly effective. For domain-specific training, transfer learning is also employed [8,9]. When taught and evaluated for a variety of species, the results suggest that it is more accurate. It was demonstrated that transfer learning to another location may be accomplished using herbarium datasets, even when the species do not match.

Lu et al. (2017) presented a method for diagnosing rice illness. This is accomplished using a deep convolutional neural network. There are 500 pictures in the dataset utilized for the research. For identifying reasons, ten different kinds of rice disease are employed. 95.48 percent accuracy was attained during this process.

Gan et al. (2018) have completed an essential task of mapping citrus yield [9]. To determine if the fruit is ripe or not, an image-based method is utilized. Green fruit is detected using a combination of color and thermal images. For the categorization of ripened and green fruit, the CTCP algorithm, also known as color thermal combined probability algorithm, is employed.

Liang et al. (2019) used a severity estimation method to determine the degree of illness in a plant. For diagnosing the illness, the PD2SE-Net method has been developed. During the identification phase, the visualization and augmentation processes are carried out. As an add-on structure, the ResNet50 architecture is employed. For illness severity, the accuracy is 0.98 and 0.99.

Chapman et al. (2018) used data from an oil palm farm to use a Bayesian network to forecast yield. The accuracy and r2 (0.6 and 0.9) scores for this network are greater [10]. The Bayesian network's parameters were described in detail. Five distinct classes methods were used to measure the depth of the soil.

A method for detecting wheat leaf rust has been presented by Azad Bakht et al. (2019). It's time to calculate the leaf area index. At various levels, the canopy-scale is examined. For identification, machine learning techniques such as boosted regression tree, Gaussian process regression, support vector machine, and random forest approaches are utilized.

Iqbal et al. (2018) did a study focusing on citrus plant disease and the categorization of the many diseases that affect citrus plants. It also goes through the many techniques utilized in the segmentation, feature extraction, feature selection, image processing, and classification methods in depth. It also goes into the automated technologies that are used to detect and classify items [10,11]. Citrus disease is known by several names, including canker, black spot, citrus scab, melanosed, and gearing. For illness extraction, the K-mean method is employed, and the approaches used for each stage of analysis are compared to the current survey. Color features are computed and classified using the Back Propagation Neural Network (BPNN) and the Grey Level Co-Occurrences Matrix (GLCM).

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Pre-processing, color-based transformation, picture improvement, noise reduction, resizing, and segmentation techniques are all covered. Various texture, color, and shape-based feature extraction techniques are used. It contains an overview of several classifier techniques as well as their applications. According to the findings, the pre-processing approach increases segmentation accuracy.

Kaya et al. (2019) discovered that manually categorizing data has several key drawbacks, including the fact that it is costly, time-consuming, and requires expertise. During the classification phase, a Deep Neural Network is offered as a solution. Plant categorization model performance has increased. It contains a comparison of several methods and their best results, such as (DF-VGG16/LDA = 99.00, DF-Alex net/LDA = 96.20, CNN-RNN = 98.80, CNN = 99.60, (CNN, SVM = 97.47)). Input, 3*3 conv, ReLU, pool, 3*3 conv, ReLU, pool ReLU, FC-class size, SoftMax are all part of the proposed CNN design. The classification accuracy for each model in the training dataset and for the pre-trained model is shown in the image.

It takes the image as input and assigns different weights to the various items in the image, making each object distinct from the others. The pre-processing burden in the convolution neural network is minimal when compared to other classification techniques [12]. Neuron connection in the human brain is analogous to the neurons linked to CNN. It could learn its filters. The dependencies existing in the spatial and temporal components are captured with the help of the applicable filter. During the process, it plays a vital role in reducing the picture to simpler forms, with no image loss. Object detection (R-CNN, Fast R-CNN, and Faster R-CNN) and semantic segmentation are two major applications of convolution neural networks (Deep parsing network, fully convolution network). CNN architectures are made up of a series of layers that change one activation volume to another with the aid of differentiable functions. CNN is primarily built with layers like as convolution, pooling, and fully linked. CNN's essential component is the convolution layer. It carries the network's computing workload. Dot products are mostly performed between the kernel and the limited region. The depth is large in the kernel, while the spatial is less. In kernel, just the depth will be increased, while the height and width will be reduced. Image representation is achieved by sliding the kernel over the image's height and breadth (Hang et al., 2019). Secondly, support vector machine techniques are utilised with both RGB pictures and spectral reflection for the detection and quantification of tomato leaf miners. Thirdly, tomato powdery molten fungus Oidium neolycopersici is identified by utilising SVM algorithms and visual thermal and stereo light. Fourthly, powdery mildew is found in tomatoes with self-organizing maps and RGB pictures. In this work we just utilise 138 images, a modest number of images to get the data set variability [13]. Most of the disease detection and classification classificatory were developed using few data sets relying on image extraction to categorise the leaves. In order to create reliable image classification, a big, labelled and validated collection of pictures of sick and healthy plants is needed. No dataset with these characteristics was accessible until quite recently. The PlantVillage initiative has already begun to gather and classify tens of thousands of illustrations of normal and sick plants to address this problem. The PlantVillage dataset is used for building deep neural networks for the diagnosis of various crop diseases [14]. It is used with the most recent pest identification and machine learning research projects.

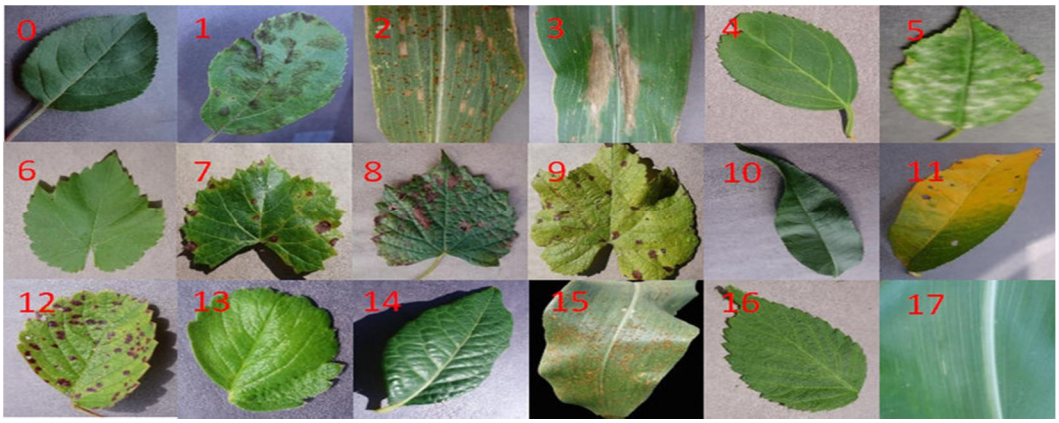

Figure 2: PlantVillage Dataset

Figure 2 depicts the PlantVillage dataset. It consists of 54306 healthy and unhealthy leaf images divided into 38 categories by species and disease.

Farmers may use several apps to forecast crop yields depending on meteorological variables. In order to anticipate crops, machine learning techniques have been utilised. For the five climate factors the Random Forest Algorithm is used to train the model, however additional inputs like as soil quality, pest, chemical materials utilised are not taken into account. The model was taught to build random forest by 200 decision-making trees.

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This approach is based mostly on weather forecasts, plantations of crops, crop forecasts, and crop costs. For this model, the data set for economic farming is analysed [14,15]. It is then pre-processed and divided into training and test data. For excellent precision, Support Vector Machine and random forest methods are employed. The final result is to forecast crop yields and to designate crop yellow yields as the best bio condition. In the developing country it is hard to achieve smart farming since many farmers do not know the technologies and are uneducated.

There were four types of agricultural yield predicting methods or combinations: (a) field investigation, (b) plant growing modelling, (c) remote sensing, and (d) statistical models. The merits and disadvantages of these techniques. Field surveys attempt to detect the reality of the ground using farmers' reports and objective surveys. Due to sampling mistakes and non-sampling, these studies suffer from decrease in replies, resource constraints and dependability [16]. Process-oriented crop models simultaneously increase crops and develop crop by inputs depending on crop characteristics and environmental circumstances. They employ agro-growth and development concepts, which apply throughout time and space. However, all yield reduction variables are not taken into consideration and substantial data and validation needs are present. Remote sensing attempts to get current crop information via satellite pictures. Remote sensing information is available internationally and does not suffer from human mistakes under open data regulations. Satellite data readings only offer indirect measures of the agricultural yield, specifically measured irradiance, so as to translate satellite data into yield predictions on physicochemical or analytical frameworks. Statistics models employ weather indicators and predictors for the results of the three preceding techniques [16,17]. These models assess the yield rate trend for the development and management of genetics and fit linear models between predictors and residues. They offer high precision, but cannot be expanded into various space and time settings. Reusability in agricultural system modelling was not a design objective; the underlying science has been given more attention. Examples of machine applications that learn to forecast agricultural production are similar in design. Methods have not been concentrated on reusability or transferability. Our machine learning platform has been developed to focus on flexibility and reusability.

III. CONVOLUTIONAL NEURAL NETWORK FOR PEST DETECTION

Convolutional Neural Networks (CNNs) fall into the deep neural network model category and have regularized multilayer perception. A completely connected network causes data overfitting. It outperforms hierarchical structures and aids in the resolution of problems. Using simple patterns to create complicated patterns is a great way to get started. In a neuronal network, the pattern of neurons is called neuronal connectivity. The biological process is analogous to the convolution neural network [17]. It requires only tiny amounts of data throughout the image classification process. It takes an image as input and then assigns different weights to the various items in the image, making each thing unique. The pre-processing task in the convolution neural network is minimal when compared to other classification algorithms. Neuron connectivity in the human brain is similar to that of CNN's neurons. It is capable of learning the filters it contains. The dependencies existing in the spatial and temporal components are captured with the help of the relevant filter. During the process, it plays a significant role in reducing the image to simpler forms, with no image loss.

CNN architectures are made up of a series of layers that translate one activation volume to another using differentiable functions. CNN is primarily built using layers such as convolution, pooling, and fully connected. On CNN, the convolution layer is the most important component. The network's computational load is carried in it. Between the kernel and the limited region, it primarily executes dot products. The kernel has a large depth but a tiny spatial dimension. In kernel, only the depth will be increased, but the height and breadth will remain tiny. Image representation is achieved by sliding the kernel in the image's height and breadth.

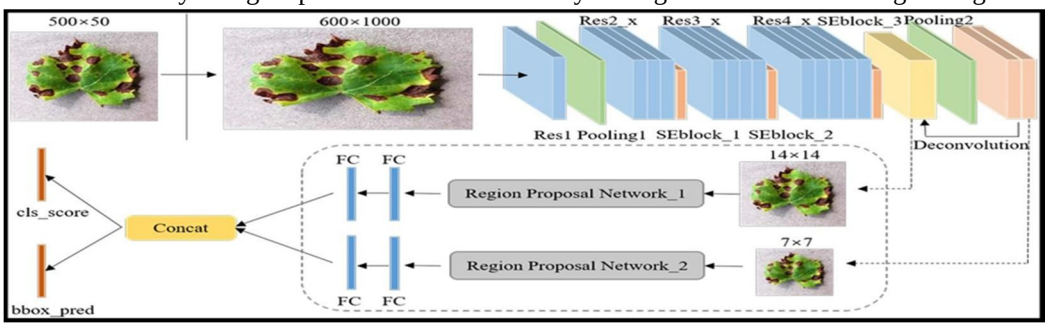

Figure 3: Convolutional Neural Network for Pest Detection

A CNN model is trained with a class label dataset and then finally tweaking it by utilising just a few instances from the target domain dataset as shown in Figure 3.

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IV. PROPOSED METHOD

The proposed solution is an android application. In Plant Disease detection the image of the plant is simply taken and uploaded to the mobile device. Then this image is supplied by a Convolutional Neural Network encoding this image in a numerical array, which is classified in the model with the other numerical arrays. The model is a TensorFlow model, which is built from the huge size of the conventional TensorFlow model into a TensorFlow model. This model helps to categorize the numerical value of the image supplied into data sets. When a numerical array matches the trust is calculated and the trust value is displayed.

The created technology is linked with a smartphone to enhance the efficiency of farmers [18]. A CNN Object Detection model is implemented on a mobile device using the proposed system using the Keras platform to find pests in the picture. Plant disease detection includes five key steps: image acquisition, image pre-processing, image segmentation, feature extraction and grading. Digital camera or scanner is used as part of image processing, pre-processing comprises enhancing image processing, dividing pictures where the afflicted and healthy regions are divided, extracting the feature defines the area of infection and helping classify illness.

A. Dataset

For Pest Detection we have used The Plant Village dataset. It is split into 18 groups, comprising 54306 pictures of various plant leaves. This collection includes 13 plant kinds and 26 plant disease categories. The data collection includes both healthy and ill pictures of crops. Fourteen crop species, including: apple, blueberry, squash, strawberry, orange, peach, pepper, potato, raspberry, soy and tomato, are shown. The two areas for each class are the plant name and illness name. As shown in Figure 4 all the pictures are scaled and divided for further categorization and pre-processing.

The Pest Detection module follows the following steps:

1) *Image Acquisition:* Image acquisition is the collection or collection procedure with and without illness of plant leaf pictures. The system's accuracy depends mostly on the picture kinds utilised, as training is carried out. Images are taken from or collected using a digital camera on the farm [19]. The quality of the image relies on the kind and orientation of the digital camera employed. The first procedure is to acquire the picture data that is utilised as a computational input. Image data entry in .bmp,.jpg,.png,.gif format should be provided.
2) *Image Pre-processing:* Pre-processing of the picture follows acquisition of the image. Image pre-processing refines images by noise, enhance, resize, increase data, cuts, convert colour space, smoothing etc. images. The recorded leaf pictures might reveal insects, insect faeces, dust and squirrels etc. that are all thought to be eliminated noise as shown in Figure 4. Enhanced distorted pictures with noise reduction filters that eliminate distortions [20]. Contrast improvement techniques are required if the image contrast is poor. The job requires just sheet pictures and the rest of the pieces are regarded as the backdrop. Hence, approaches to remove background leaves from entire pictures are utilised for removing them.
3) *Image Segmentation:* In the identification of leaf diseases, the segmentation of picture plays an essential role, as pre-processed images are taken from the area of interest. The division of the picture into distinct portions of a leaf requires the division of the image. Segmentation may be carried out by utilising several approaches, such as Otsu, k-means, thresholding, region, edge, etc [21]. Deformation segmentation takes the intensity values into account when splitting photographs and this is an example of edge detection. Colour variations are seen in infected leaves and such leaf pictures are broken off using the clustering process k-means to remove sick parts from the leaves.
4) *Feature Extraction:* The extraction procedure involves the identification and extraction of intrinsic properties known as image disease descriptive features. Colour, texture and form characteristics are generally extracted. Colour characteristics distinguish between one illness and another based on colour and are main colour aspects of the histogram and moments [22]. For the categorization of diseases, textures that indicate how picture textures are dispersed are retrieved. Examples of textural characteristics include entropy, homogeneity and contrast. The form shows how the symptoms of the disease differ from each other. For leaf diseases, structural extraction is better than colour and texture.
5) *Disease Classification:* As shown in Figure 4, the collected characteristics are utilized for the categorization of leaf diseases. Classification is a monitored approach for mapping pictures from leaves to various disease classifications [23]. The classifier technique produced describes the predetermined set of illness classes by learning from pictures with disease labels as shown in Figure 4. This phase of learning is known as the stage of training. The trained classifier is used to test the pictures and the precision achieved is dependent on the trained classifier.

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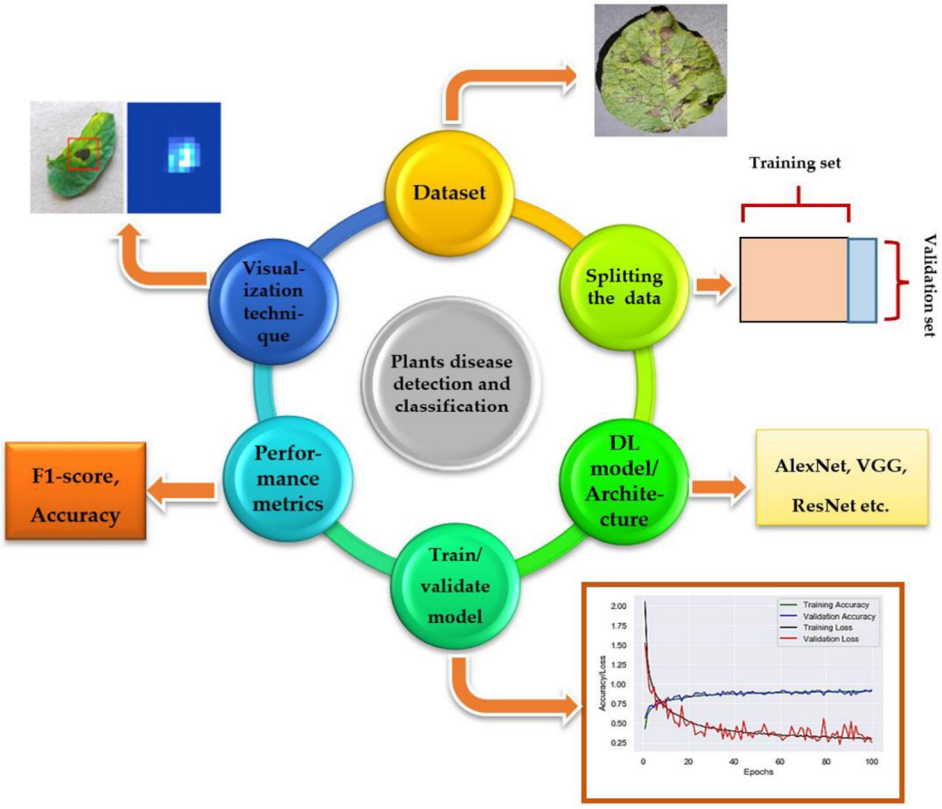

Figure 4: Flowchart for Pest Detection

V. COMPARISON BETWEEN DIFFERENT PEST DETECTION TECHNIQUES

Table 1 shows the comparison between different Pest Detection techniques based on the classification methods used, name of the disease and accuracy obtained.

REFERENCE	CLASSIFICATION METHODS	PLANT	DISEASE	RESULT
[1]	1. Support Vector Machine	Grape	Scab and Rust disease	80% accuracy
[2]	2. Artificial Neural Network	Apple	Infected	82% accuracy
[6]	3. Neural Network	Cotton	Cercospora, Red Spot	89.56% accuracy
[8]	4. Fuzzy KNN	Tomato	Nutrient deficiency	More than 83.5% accuracy
[9]	5. Feed Forward BPNN	Grape	Downey Mildew	85% accuracy

Table 1: Comparative Study of different Pest Detection Techniques

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VI. RESULTS AND DISCUSSIONS

The image of the leaf can be taken and sent to the android device in the pest detection module. After this the model will predict the type of pest in the leaf. As shown in Figure 7, for the pest detection model, the accuracy of the model obtained is 95.16%. Also, the confidence value is determined and the value of the confidence is presented if a numeric array matches.

In the android application, the user can check pest in the plants via:

A. Camera
B. Gallery
C. Live Detection

The performance metrics that are considered in our proposed work are as follows.

1) *Performance Accuracy:* The total number of correctly classified images to the total number of images.
2) *Loss Function:* How well the architecture models the data.
3) *Precision:* The ratio of the number of correctly predicted observations (true positives) to the total number of positive predictions (true positives + false positives).
4) *Recall:* the ratio of correctly predicted observations (true positives) to all observations in that class (true positives + false negatives).
5) *F1 Score:* the Harmonic Mean between precision and recall.
6) Time requirement (in sec) per epoch for training each DL model.

The output is as follows:

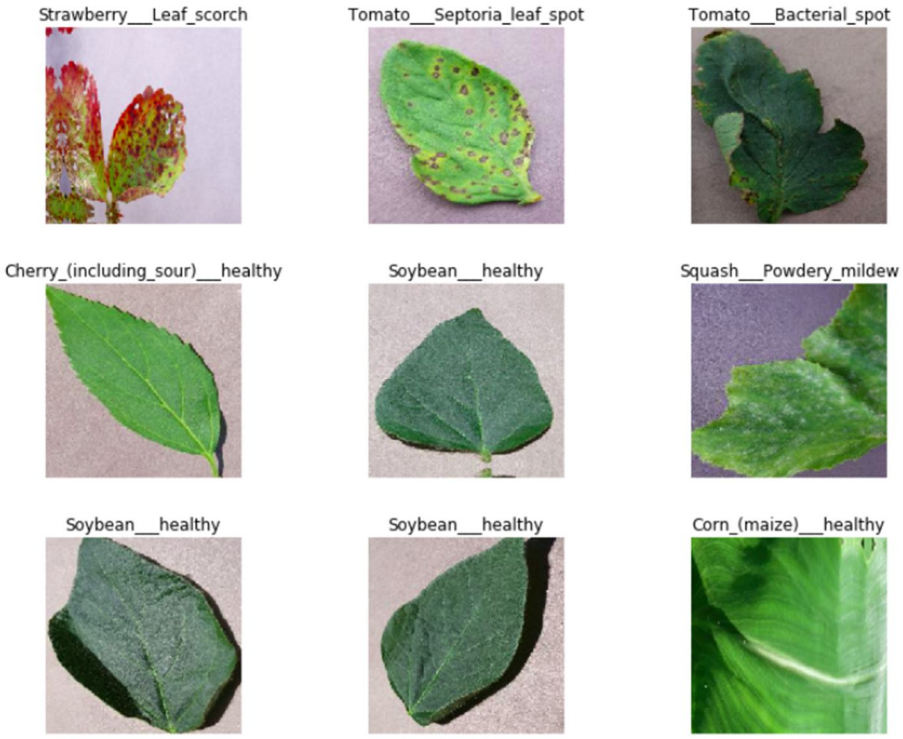

Figure 8 represents the detection of pest in Tomato plant and the name of the pest is Septoria leaf spot.

Considering four fundamental classification metrics:

- validity,
- precision,
- recall, and
- f1 scores,

the total performance of the system designed for pest recognition is evaluated.

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In addition, a comparison is made with the performance of earlier research, i.e., neural network back propagation (BP) and single-shot detector (SSD) MobileNet, for the outcome of the pesticide categorization. These findings corroborate the results in order to detect automated agricultural pests from our suggested Faster CNN. The SSD MobileNet was successful in determining all the pictures of pests that have been examined.

But the Faster CNN suggested achieves the greatest mean precision value (98.0%) over BP's and SSD's 50.0%, and SSD's 86.0% respectively. respectively, the Faster CNN offered. Furthermore, our suggested Faster CNN model's prediction accuracy has been validated for multiple sizes of pest pictures evaluated, by altering the percentage of data divided into 70–30% and 90–10% for training and tests. Normally, by expanding from 70% to 90% of the complete data set the performance of agricultural pest classifiers is enhanced. Both BP neural network and SSD MobileNet classification accuracy rose to 43.0% and 85.6%, respectively, for 30% testing data, but our proposal Faster CNN's accuracy rate remained high at 94.0% at the same test data amount.

VII. CONCLUSION

The aim of this paper is to identify illnesses in crops by means of the deep learning method, which is the Convolutional Neural Network. The model is essentially evaluated for certain species of plants with certain kinds of plant diseases. The template was built using tensor flow, Keras and Android. The total system findings indicate that the MobileNet model functions better than other models and provides improved accuracy in illness detection. The number of plant types and their diseases will expand as an addition to the project. The model will also be enhanced by increasing the training and testing parameters. Without involving any middlemen between farmers and consumers and earning profit, farmers/customers may sell/purchase farm products at an ideal cost. Farmers will find it more helpful to know information about existing farms and feel it is a safer and more valuable website. In order to propose optimal harvests with greater precision and productivity the framework uses supervised machine training algorithms. The model is trained to validate the performance of the current model created using ANN with decision-tab classifier. The accuracy values of the measured values have shown a better 95 percent accuracy suggestion model built using ANN compared with 92 percent accuracy achieved from decision book classification systems. In addition, with bigger datasets, ANN performs well.

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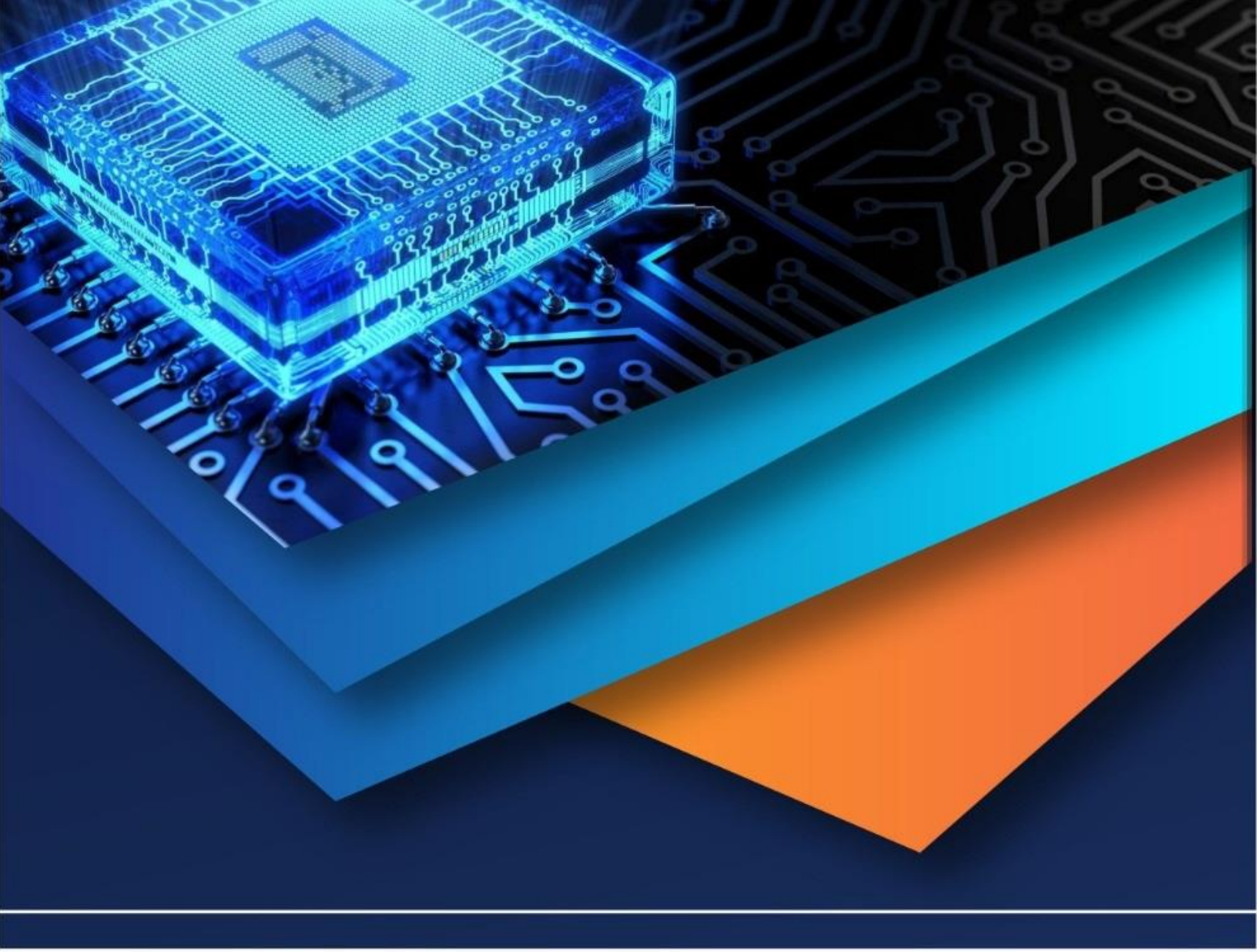

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