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ENHANCING AGRICULTURAL SUSTAINABILITY THROUGH AI-POWERED IMAGE PROCESSING: A COMPREHENSIVE STUDY ON PLANT DISEASE DETECTION

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ABSTRACT :Agriculture, one of the oldest human occupations, has seen significant technological advancements to address the challenges posed by a growing population and limited farmland. In India, the agriculture sector employs over 50% of the workforce and contributes around 17-18% to the GDP. However, plant diseases cause substantial economic and production losses, particularly in developing countries. Traditional disease detection methods, which rely on manual observation, are labor-intensive and impractical for large-scale farms. Recent advancements in artificial intelligence (AI) and image processing offer transformative solutions to these challenges. AI-powered image processing can enhance the accuracy and efficiency of plant disease detection, enabling early intervention and better management of crop health. These technologies involve steps such as image acquisition, preprocessing, segmentation, feature extraction, and classification, providing a cost-effective alternative to traditional methods. For instance, Convolutional Neural Networks (CNNs) have demonstrated high accuracy in detecting and classifying diseases in crops like tomatoes. Despite challenges such as complex backgrounds and varying disease characteristics, AI models can effectively manage these issues through advanced algorithms and data augmentation techniques like Generative Adversarial Networks (GANs). The integration of AI and image processing in agriculture not only improves disease detection but also supports precision farming, contributing to increased crop yield and quality. This research underscores the critical role of AI and image processing technologies in sustainable agriculture, highlighting their potential to mitigate economic losses due to plant diseases and enhance global food security.

Keywords: ***GLCM, SVM, KNN, Genetic Algorithm (GA), Radon Transform (RT)***

Introduction

Agriculture is one of the oldest occupations in the world. Over the millennia, humanity has come a long way in the manner in which the crops were farmed and have introduced several new technologies to grow crops. Due to rapid growth in population, the farming land has become scarce which paves the way to use more creative and efficient ways to farm using less land, to produce more yield.According to India Economic Survey 2018, agriculture sector employs more than 50 percent of the total workforce in India and its Gross Domestic Product (GDP) contribution is around 17-18% AI technologies to help farmers improve their yield by making the crops healthier. The major economic and production loss in agriculture is caused due to plant diseases. Plant diseases reduce both the quality and quantity of the agricultural product and has become a nightmare to developing countries as it influences the economy of country which rely on agriculture. According to Pimentel (2005), in United States crop losses due to pathogens is estimated approximately around $ 33 billion every year in which around 65% ($ 21 billion) is attributed due to non-native plant pathogens.According to Roberts et. al. (2006), soybean rust which is a type of fungal disease caused in soybean has caused a significant economic loss. It is estimated that, by just removing 20% of the infection, the farmers would have got a profit of $ 11 million approximately.

Recent study also shows that every year around 30% of crops are lost in the production chain (Flood 2010). In USA, the fungal diseases in crops after pre and post-harvest have caused a loss annually which exceed $ 200 billion, and over $ 600 million are annually spent on fungicides alone (González-Fernández et. al. 2010). According to the study in Georgia in the year 2007, around $ 539.74 million were spent on crops of which $ 185 million was spent to control the diseases alone. In 2010, approximately $701.2 million was spent on plant diseases which includes the control cost. The total cost of the crop production was estimated around $ 4236.51 million, in which 16.5% of it accounts for disease loss.

In India, the estimated annual losses due to nematodes is approximately $ 330 million. This shows that plant disease management is crucial for the stable production of food (Bentley et. al. 2009). In the year 2000 to 2001, less than 25% of Malawi farmers attained self-sufficiency in maize cultivation (Devereux 2009). The above facts show that, population which are dependent on a particular crop is at risk, since the crop failure due to disease can lead them to famine (Mahlein 2016). This has prompted the urgent need to evaluate the quality of plants to identify any disease in them. In fact, around 60 to 70 percent of the disease appears only in leaves (Dhingra et. al. 2018).

Successful crop cultivation is achieved by continuous monitoring for detecting diseases. Traditional monitoring involves relying on naked eye observation by experts. This method is too expensive as it requires continuousnmonitoring by experts and will be difficult for large farms. Moreover, in developing countries, rural areas lack experts which force farmers to go long distance for consultation which is a time consuming process. Agricultural consultants provide advice to farmers on topics such as farm management, crop rotation, soil conservation, animal breeding and nutrition, the use of modern machinery, and marketing.

MOTIVATION FOR THE WORK

Economy of developing countries like India mainly rely on agricultural products (Prasad et. al. 2016). Agriculture, apart from feeding the ever-growing populations has become much more than that by becoming an important source of energy, and helps to solve the problem of global warming. There are several pathogens that affect plants with the potential to cause devastating social, economic and ecological losses. According to Jayme (2016), plant disease identification is one of the most fundamental and important activities in agriculture. In most cases, detection is done manually, either visually or by microscopy. Since visual assessment is a subjective task, it is susceptible to cognitive and psychological phenomena that may lead to optical illusions and bias, and ultimately to error. Laboratorial analyses, on the other hand such as the molecular, immunological or pathogen culturing-based approaches are often time consuming, failing to offer answers in a timely manner. In this context, it is compelling to develop automatic methods capable of identifying diseases in a timely and accurate manner. Manual observation requires continuous monitoring of plants which are impractical and expensive for large farms. Bock et. al. (2010) highlights few drawbacks associated with manual observations such as:

- Decrease in accuracy due to tiredness and lack of concentration of observers
- Observers are susceptible to illusions
- Intra and Inter observer variability
- Frequent training to observers to maintain quality, which is expensive
- Need for standard handbooks which helps in assessment

Contrary to manual detection techniques, automatic detection of plant pathology is easier, cheaper and economical for large farms. There are various algorithms proposed for plant disease detection using a leaf image. Traditional algorithms are classified based on leaf shape, leaf veins, leaf margin and leaf texture. The majority of automatic methods proposed so far rely on digital images, which allows the use of very fast techniques. However, extrinsic and intrinsic factors affect the performance and make these methods error prone, which was the motivation for the current research. Some of the extrinsic factors which affect the performance (Camargo & Smith, 2009a) are:

- Complex background which makes it very difficult to correctly segment the region of interest (ROI) where the symptoms are present.
- Capture conditions which are difficult to control, make the images to present characteristics that are difficult to predict and make the disease identification more challenging.

Apart from it, the intrinsic factors which impact the performance are:

- Symptoms with gradually fading boundaries rather than well-defined boundaries, makes it difficult to clearly define healthy and diseased regions.
- Varying disease characteristics depending on the stage of development for a given disease, and sometimes based on where it is located on the plant.
- Difficulty in identifying symptoms produced by different diseases which may be present simultaneously, manifesting either physically separated or combined into a hybrid symptom.
- Similarity among symptoms, produced by different diseases, which forces the methods to rely on very tenuous differences to discriminate among them.

According to Camargo and Smith (2009b), the rate of spread of disease depends on current crop conditions and susceptibility to infection. When a plant becomes diseased, it can display a range of symptoms such as coloured spots, or streaks that can occur on its leaves, stems, and seeds of the plant. These visual symptoms continuously change the colour, shape and size as the disease progresses. The crop yield can be increased by using a reliable approach to detect plant pathogens such as Computer-Aided Diagnosis (CAD) instead of expert's individual observation as it reduces the cost since mobile phone is commonly used. Machine learning technique can successfully be used for disease detection and classification mechanism. This help the farmers to analyse a variety of things in real time and helps them take better decisions. Precision agriculture uses AI technology to aid in detecting diseases in plants, pests, and poor plant nutrition on farms. The typical CAD architecture consist of image pre-processing, region of interest identification, feature extraction, selection and classification (Doi 2005) as shown in Figure 1.1.

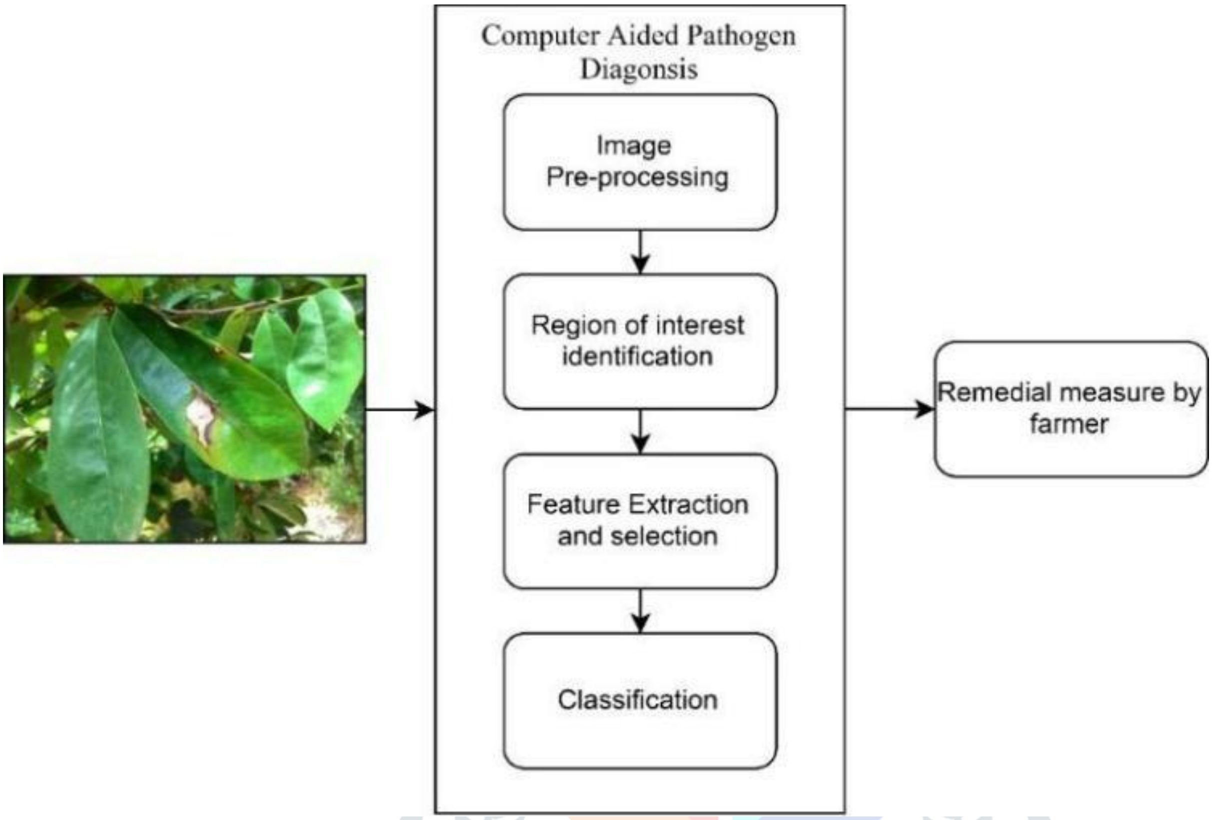

Figure 1.1 Schematic diagram incorporation of CAD system into agricultural pathogen diagnosis

OBJECTIVE OF THE WORK

The main objectives of the research work are

- To segment the diseased region from the leaf
- To identify the best features those contribute to classification of the diseased and the healthy leaf.
- To improve classifier performance to classify healthy leaf or specific leaf disease.
- To formulate deep learning model that improves classification performance without using handcrafted features.

DATASET USED IN THE WORK

The datasets are collected from the PlantVillage online repository, which is dedicated for plant disease detection (Hughes & Salathe 2015). More than 54,000 images cited by pathology experts for different types of crops were available in the repository (available at www.plantvillage.org).The images are snapped using standard point and shoot camera under supplemental light, either in sunny or cloudy conditions so as to imitate the real-time situations. The photos are pictured using smart phones at the research stations of Land Grant Universities in USA. The fourteen different type of plant varieties present in the repository are apple, corn, grape, orange, blueberry, cherry, soybean, squash, peach, bell pepper, potato, raspberry, strawberry and tomato. The species includes 17 fungal diseases, 2 viral disease, 4 bacterial diseases, 2 mold diseases, and 1 disease caused by a mite.

In order to validate the proposed methodology, a new dataset was also created manually from the field, using a mobile camera which has 8 mega pixel camera resolution. The resolution is selected keeping in mind the present day basic mobile phone having fewer pixels, which a farmer can easily afford. The plant leaf which is chosen for the analysis is soursop (also known as graviola, prickly custard apple, Tamil: aathappazham) which is a species of the genus annona of the custard apple tree family. It is a small, upright, evergreen tree that can grow to about 4 meters (13 ft) tall. The motive behind selection of this leaf lies in the medicinal value of the plant leaves, root, bark and fruit. It is widely believed that soursop fruit act as the effective medicine for the treatment of cancer, however there is no credible scientific evidence that the extract can prevent, cure, or treat cancer. Soursop extracts can kill some types of liver and breast cancer cells that are resistant to particular chemotherapy drugs, but have never been proved on humans (Damle 2015). Dataset consists of around 1250 leaves with 700 diseased leaves and the rest as healthy leaves. The images were captured in the field condition with normal day light condition with no special effects given during the capture of the image. This is done so as to validate various algorithms in the real time field conditions. In addition to this, around 200 images of different plant leaves have been downloaded from various online sources and the performance of the algorithms is analysed. Analysis of the proposed work have been carried out using the images of plant leaves obtained from the above mentioned databases. Table 1.1 summarizes the different plant leaf used to analyse various proposed techniques.

Total No. of Samples	**Disease Common Name**	**Disease Scientific Name**	**Disease Type**
Apple (Malus pumila)			
	Cedar apple rust	Gymnosporangium Juniperi Virginianae	Fungi
6461	Apple scab	Venturia Inaequalis	Fungi
	Black rot	Botryosphaeriaobtuse	Fungi
Cherry (Prunus avium)			
1906	Powdery mildew	Podosphaera spp	Fungi
Corn (Zea mays)			
	Leaf spot	Cercospora zeae maydis	Fungi
6176	Common rust	Puccinia sorghi	Fungi
	Northern leaf blight	Exserohilum turcicum	Fungi
Peach (Prunus persica)			
2657	Bacterial Spot	Xanthomonas campestris	Bacteria
Soursop (Annona muricata)			
1250	Anthracnose	Glomerella cingulata	Fungi
Strawberry (Fragaria ananassa)			
1565	Leaf scorch	Diplocarpon earlianum	Fungi
Grape (Vitis vinifera)			
	Black rot	Guignardia bidwellii	Fungi
4063	Black measles	Phaeomoniella	Fungi

Total No. of Samples	Disease Common Name	Disease Scientific Name	Disease Type
	Leaf spot	Pseudocercospora vitis	Fungi

Table 1.1 Summary of dataset of different plant leaves used

(a)

(b)

(c)

(d)

(e)

(f)

(d)

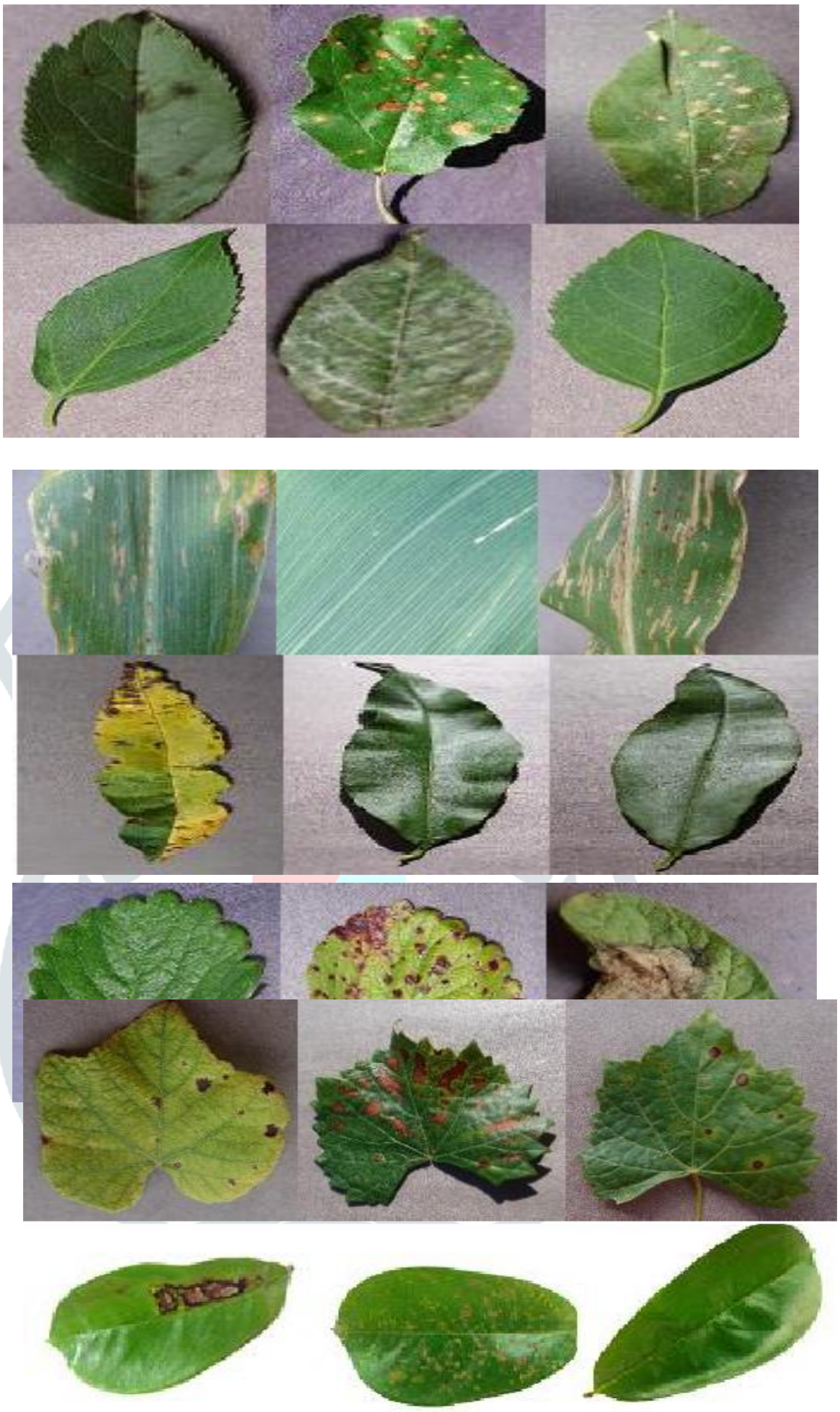

Figure 1.2 Samples of dataset images (a) Apple (b) Cherry (c) Corn (d) Peach (e) Strawberry (f) Grape (d) Soursop

FEATURES

Analysis of any image usually involves examining a large set of similar images for a particular applications. The raw data is examined to get some understanding about the image. But the information provided by the raw data is very huge. The information acquired contains both useful and useless information for a particular application. In pattern recognition and image processing, feature extraction is an important step which act as a dimensionality reduction. The large dataset to be processed contain redundant data and it is transformed into a reduced set of feature representations. The process of transforming the input data into a set of features is called feature extraction. Some commonly used features are GLCM, shape, edge, boundary, texture, colour, etc. There are several techniques available for feature extraction from images and few are listed as below:

GLCM Features

Gray level co-occurrence matrices (GLCM) proposed by Haralick has become a widely used texture measures in image processing and pattern recognition problem. GLCM is also known as gray level spatial dependence matrix. It is a statistical method of examining texture that considers the spatial relationship among the neighbourhood pixels. Texture is a surface property and is one of the most important characteristics of an image. The spatial arrangement of intensities in a picture is described by image texture. When it comes to texture, a simple one-dimensional histogram is useless. Images with the same histogram, but distinct textures are possible. The Haralick measures were used to extract the useful texture information from the co-occurrence matrix. Haralick proposed a statistical method for textural feature extraction which are derived from the co-occurrence matrix (Haralick et. al. 1973). It is characterized by analysing how frequently pairs of pixel with specific gray values and in a specified spatial relationship occur in an image. The data obtained from the above method is known as GLCM. The required features are extracted from the GLCM matrix which provides information about the inter- pixel relationship. GLCM for four different orientations 0°, 45°, 90°, and 135° at a distance of 1 are computed and features are extracted. Figure 1.3 summarizes the GLCM parameters used in the proposed work.

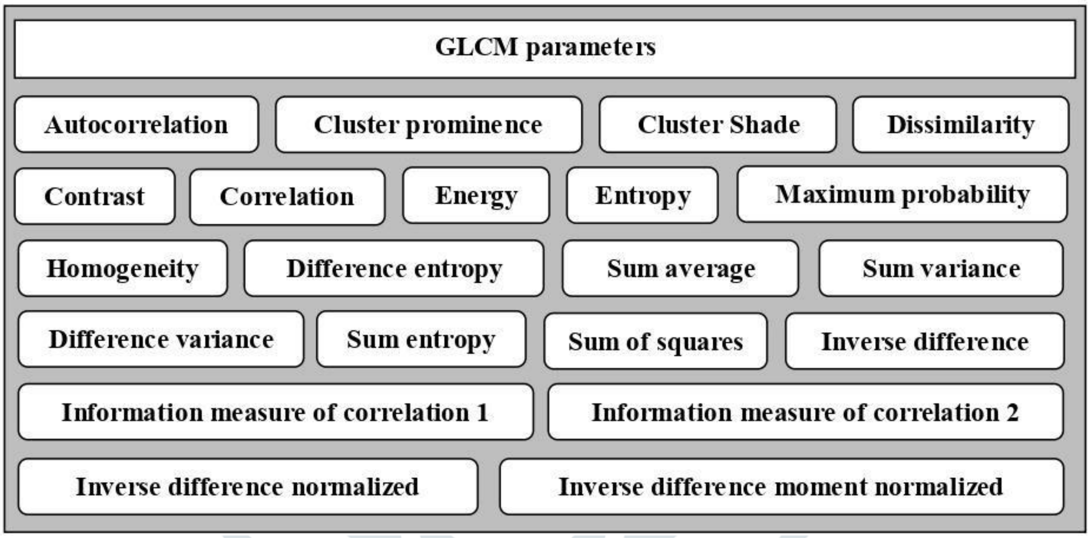

Figure 1.3 GLCM features

Statistical Parameters

Statistical parameters are mathematical properties of a set of numerical values. These are typically real numbers. Since the input is random, statistical analysis has been undertaken. Statistical analysis aids in the study of picture intensity fluctuation. The statistical parameters which are considered for analysis are mean, standard deviation, skewness, kurtosis, fifth central moment and sixth central moment (Patil and Udupi 2011).

FOCUS OF THE WORK

The course of entire research work investigates computer aided classification and detection of leaf diseases. The research documented in this thesis is highlighted below:

Segmentation of leaf diseases based on Crest Factor

A novel method to detect the disease spots in apple leaves, even under the influence of specular noise is proposed. GLCM features are extracted from the segmented region and given as input to the classifiers such as support vector machine (SVM), K-nearest neighbour (KNN) and Tree. An average accuracy of 97.9% is achieved using SVM classifier.

Segmentation of leaf diseases based on Genetic Algorithm

Genetic Algorithm (GA) which is based on natural theory of evolution is used for the segmentation of apple leaf diseases. This proposed method detects the disease spots with a smaller number of computations. The method produces an accuracy of 92%, a sensitivity of 0.9008 and a specificity of 0.9412 for back propagation neural network classifier.

Selection of prominent features for leaf disease classification based on NCM

Neutrosophic Logic (NL) based feature selection algorithm is proposed to select the dominant features that influence the leaf disease classification. Statistical and GLCM features are considered for the analysis. The proposed technique forms a feature subset with eleven dominant features to achieve an average accuracy of 99.8% for neural network classifier.

Leaf disease classification based on Neural Networks and Radon Transform (RT)

A method to classify and localize the disease location in leaves is proposed with the help of neural network and radon transform. A novel training function to improve the performance of back propagation neural network is proposed. Further the disease location of the classified leaf is localized with the help of radon transform. A classification accuracy of 95.64% is achieved for grape leaf disease detection.

Leaf disease detection and classification based on Convolutional Neural Networks

In order to overcome the problem of handcrafted features, deep learning approach based Convolutional Neural Network (CNN) is used to extract features from the leaf images which is then classified using logistic regression and SVM. The method produces an top-5 accuracy of 99.93%. Further the hyper parameter of the CNN model is tuned for the state-of-the-art deep learning models by varying mini-batch sizes and optimization function. Hyper parameter tuned ResNet50 with stochastic gradient descent (SGD) optimization and mini-batch 32 produces an accuracy of 96.61%. A novel CNN model based on Visual Geometry Group (VGG) model is proposed which produces an average accuracy of 99.35%. All the models are trained on 38 different type of diseases obtained from PlantVillage database as well as using the manually collected soursop images.

CONCLUSION

The integration of AI and image processing technologies offers a transformative solution to these challenges. AI-powered image processing can significantly enhance the accuracy and efficiency of disease detection in crops. These technologies utilize steps such as image acquisition, preprocessing, segmentation, feature extraction, and classification to identify diseases accurately and quickly. This not only helps in early disease detection but also supports precision agriculture, allowing for better management of plant health. For example, Convolutional Neural Networks (CNNs) have been used to detect and classify diseases in crops like tomatoes with high accuracy, providing a cost-effective alternative to traditional methods The use of AI and image processing in agriculture addresses both extrinsic and intrinsic challenges associated with plant disease detection. Extrinsic factors such as complex backgrounds and varying capture conditions can be managed more effectively, while intrinsic factors like symptoms with gradually fading boundaries and varying disease characteristics at different stages are better handled through advanced algorithms. Moreover, data augmentation techniques like Generative Adversarial Networks (GANs) help mitigate data scarcity, further improving the robustness of AI models.In conclusion, the adoption of AI and image processing technologies in agriculture is essential for sustainable crop production. These technologies offer precise, efficient, and scalable solutions for plant disease detection, significantly enhancing crop yield and quality. By leveraging these advancements, farmers can better manage plant health, reduce economic losses due to diseases, and contribute to global food security.

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