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Detection and Classification of Plant Diseases by Alexnet and Googlenet Deep Learning Architecture

M.Tech. Scholar Sumit Sharma, Prof. Hemant Kumar
Department of Microelectronics and VLSI design
Technocrats Institute of technology Bhopal
sumit14sharma1995@gmail.com, hemantjec2009@gmail.com

Abstract- In this work, we have a plant disease detection system with the help of imaging technology that automatically detects the symptoms displayed on the leaves and stems of the plant and grows healthy plants on the farm Suggests that it helps. The system monitors all changes observed in plants and characteristic features such as leaves and stems, automatically identifies the changes and notifies the user. This work provides an evaluation study of existing disease detection systems in plants. The latest development of the deep learning-based convolutional neural network (CNN) has vastly enhanced accuracy of image classification. Driven by CNN's success in image classification, this Thesis based on the pre-trained deep learning-based method for detecting plant diseases. The contribution of this work has two aspects: The most advanced large-scale architecture, such as AlexNet and GoogleNet. AlexNet and GoogleNet Pre-Trained model proposed model was trained and tested on data sets collected from kaggel website. Training, testing and experimental results show that proposed architecture can realize and higher GoogleNet model getting is 99.10 %.accuracy as compare to other model.

Keywords- Plant disease detection, image processing, image acquisition, segmentation, feature extraction, classification. AlexNet, GoogleNet.

I. INTRODUCTION

The field of image processing is a multi-method one. Image data collection, pre-processing, segmentation, analysis, image definition, and real-world identification and classification are among the steps required. Image processing, also known as machine learning, is a growing field plagued by problems, particularly in the development of artificial and intelligent systems that digitize information and data using images. Machine learning is the recognition of incorporation into industry, automation, and architecture. New advances in computing have automated image processing and machine learning.

Data processing for information collection, essential agricultural tasks, observation of events, and interaction with the environment, brain communication, process control, and other practical applications for the function of automation machinery learning include, for example, data processing for information collection, essential agricultural tasks, observation of events, interaction with the environment, brain communication, process control, and the like. These days are both vital and beneficial.

As a result, through the systematic implementation of IT systems, techniques, and IT such as image processing, artificial intelligence, the neural complex, and machine learning technology, the development of IT systems and techniques in "breath practice" is improving. Algorithms, weak logic, optical signal processing, and so on.

Much of this already occurs for a variety of reasons. Image processing and machine learning technologies are rapidly being used in agriculture and animal husbandry.

Agriculture is developing machine learning systems for object recognition, fruit classification, grain classification, weed detection, pharmaceutical recognition, and so on. Due to the application of newer technologies and correct input, this step involves collecting digital images in their field using digital devices such as a camera, smartphone, and extracting required features from images for further analysis using image processing techniques.

In machine learning techniques, the classification and recognition process is crucial to success. The proposed research aims to provide a comprehensive solution to rationally solve classification problems, and it has been a rapidly increasing area with continued advancements in information or image processing.

India was recently ranked second in agricultural production. Agriculture is one of the most important fields, with a major impact on the country's social and economic growth. India's agricultural land area is estimated to be about 210 million hectares. Wheat, rice, jowar, maize, cassava, kernels, and grains are only a few examples. Blueberries, oranges, plants, grapes, apples, bombs, candy, baits, sapota, fumes, and other fruits are the most important and common.

Vanilla, dragonflies, cotton, silk, tea, coffee beans, spices, and other plants are among the most common on the market.

Precipitation, soil quality and climatic conditions all play a role in farming, and any adjustments will result in lower yields. Because of the behavioral problems that these medications cause, tracking the effects of these diseases is a major concern. Invasion of viruses, bacteria, fungi, and parasites causes these plant pathogens. These pathogens or infectious agents may be autotrophs (also known as parasites) or sapprophytes (also called heterotrophs). Parasites in living cells are killed by these saprophytes, which live in dead cells. Part-time workers would still be able to thrive.

II. RELATED WORK

Many methods were used to correctly diagnose the disease in the plants in the photographs. The majority of them are concerned with image processing in general, SVM classification, K-mean, genetics, and so on. We couldn't have asked for a more positive outlook. Some researchers have recently used neural network-based methods in this area. When opposed to traditional image-processing methods, deep neural networks are effective at detecting image disease. Mango disease control is a vital part of environmental protection since it is so closely related to the health and production of the crop.

India is particularly important in today's fast-growing world. The prevalence and simplicity of certain major diseases pose major challenges in the management and control of these conditions. As a result, the most recent study is crucial. Disease is a major impediment to fruit development, resulting in both qualitative and quantitative losses.

It is important to understand the origin, persistence, and spread of the pathogens that cause disease in order to enforce management measures quickly. The various causes of the epidemic must also be recognized, and these diseases must signal the appearance of preventive or treatment chemicals, as well as their timely implementation. The most suitable diagnostic system will be used to diagnose the disease on fruit seeds efficiently and reliably. In order to reduce the loss of fruits in the region, during traffic and in the field, as well as the development of various diseases that affect fruits, detailed etiological, epidemiological, and control research is needed.

Xinda Liu et.al (2021) Infectious diseases are very important in agriculture because they are necessary for increasing yields. Recent advances in image processing provide a new way to solve this problem by analyzing disease in visible plants. However, there is not much work in this area, let alone ongoing research.

In this article, we discuss with the system the problem of disease recognition in plants in the diagnosis of disease. Compared to other types of photographs, plant photographs usually show divided lesions, different symptoms and complex backgrounds, so it is difficult to obtain discriminatory information. To promote research on the identification of plant diseases, we have compiled a database of major diseases, which includes 271 disease categories and 220,592 images.

Based on these data, we solve the problem of plant disease identification by re-evaluating the visible area and the loss to highlight the diseased part. We first calculate the value of the blocks with each section per image according to the cluster distribution of these blocks to indicate the level of discrimination per block.

Then, during a weak control exercise, we weighed the losses for each pair of patch marks to determine the study distinguishing the part of the disease. We extract the patch features from the network that has undergone weight loss training, and use the LSTM network to patch the sequence of the heavy-duty pipelines into a complete feature set. Excessive evaluation of this information fund and other public funds proves the benefits of the proposed method. We hope that this research will further advance the program for the detection of diseases in plants in the field of image processing.

III. PROPSOED WORK

Proposed model is based on deep learning algorithms are designed to analyze and detect plant disease. This Model contains leaf retrieval, image segmentation, and identification with the utilization of targeted deep learning algorithm. This study will help extract various features from plant leaf under three categories: color, shape, and texture that will be more reliable and will provide the more accurate system. Recognition System Plant disease identification includes several steps and are discussed in the proposed approach. Phases in identification of plant disease In general deep learning has always two processes to handle with image data set using Convolution Neural Network (CNN).They are training and testing model.

Accuracy of the plant diseases with various images of leaves may produce different results as mentioned in frontier results may take 30% of testing and 70% of training of same sample of leaves, whereas the precision mean and recall keeps varying according to the time interval of all the time range changes. The system used to identify plant disease operates in two main phases namely training as well as testing phase.

The training phase again is sub-divided into further phases such as taking an image from the leaf, segmenting the interested regions, extracting features followed by the classifier training. The major step in testing phase is

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identification of image as infected leaf or notIn all the methodologies depicted in the exploration were the picture of the plant leaves is resized to 256 x 256 pixels for the expectation of ailments in the leaves. Over the analyses, there are three unique renditions of the Whole PlantVillage datasets.

Transfer learning and deep feature extraction are implemented using classifiers on data sets. So, here's a brief description of how: The detailed plans of the architecture are shown in Figure 4.1 and Figure 4.2 below. It is related to transfer learning, but aims to increase the efficiency of the target learner in the target area by passing information in a separate root area. Given the many opportunities for implementation, machine learning is now a popular and exciting field. One of the reasons for the high-ranking use average has to do with the fact that its speed is readily available during training time. Transfer learning is much more convenient to implement than any CNN architecture with arbitrarily defined weights**.**

1. Module Description:

- Input Image.
- Preprocessing.
- Segmentation.
- Feature extraction
- Classification

1.1 Input Image:
The basic data structure of MATLAB is a matrix, which is made up of a set of real or complex elements. Naturally, arrays are well-suited to displaying ordered image sets, real-value, colour, or intensity data. (Arrays are suitable for complex images).

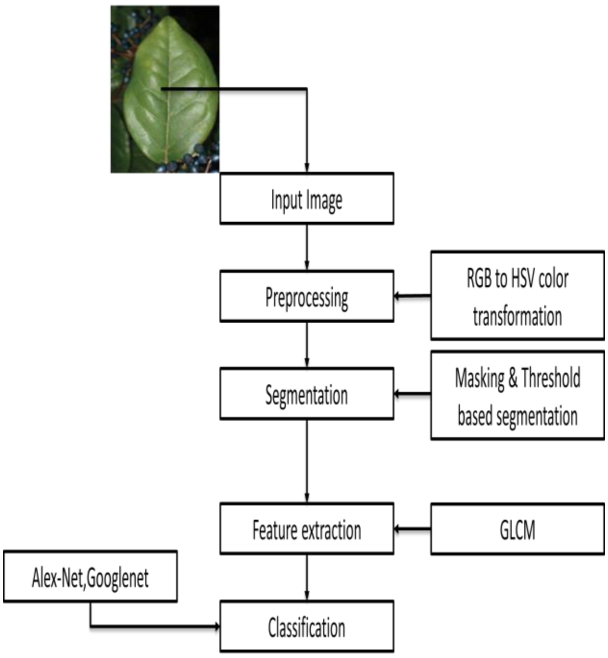

Fig 1. Proposed Diagram.

In the MATLAB workspace, most images are represented as two-dimensional arrays, with each matrix element corresponding to a single pixel in the image. For example, a 256 x 256 column image with dots of various colours can be stored as a matrix. Some images (such as RGB) require a three-dimensional array, with the first plane representing red pixel intensity, the second plane representing green pixel intensity, and the third plane representing blown pixel intensity.

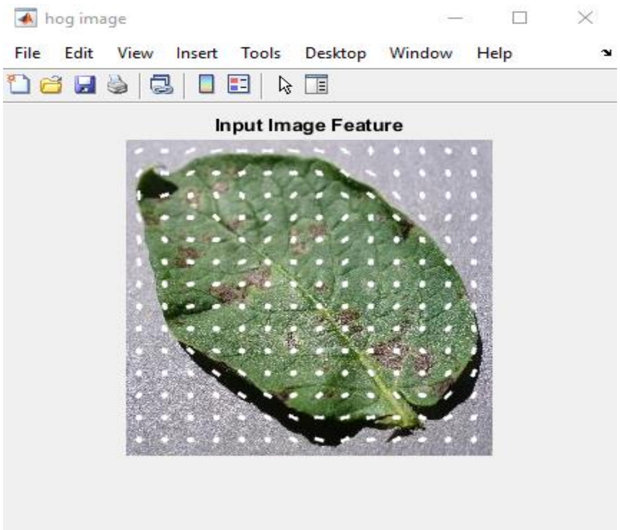

Fig 2. Input Image.

1.2 Preprocessing:
RGB images are converted to HSV color space representations. The key spectral components of each colour in the RGB model are red, green, and blue, and the model is based on a Cartesian co-ordinating scheme. While the RGB model is useful for interpreting the individual, it is not well suited for representing colours. To get around these limitations, the RGB image is converted to HSV format. After converting from RGB to HSV, the hue and saturation components are used to further analyse since they are the most educated. The RGB to HSV conversion is done on a per-pixel basis.

1.2.1 RGB to HSV color transformation-The RGB image has been converted to an HSV color space representation. In the RGB model, each color is displayed in the red, green, and blue basic spectral components, and this model is based on the Cartesian coordinate system. The RGB model matches the human eye with a strong perception of the primary colors, but this model is not suitable for describing colors in practical terms for human interpretation. To avoid these restrictions, I converted the acquired RGB image to HSV format.

1.3 Segmentation (Masking & Threshold based segmentation):
The segmentation method is divided into two stages: (1) masking and (2) threshold segmentation. I masking of green pixels Pixel masking is when the image's pixel

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value is set to zero or a different value. Since the green region of plant leaves is the healthiest, a higher rate of diseased component care is best avoided in the green sector. If the intensity of the green pixels is greater than the default value, all of those values are set to zero.

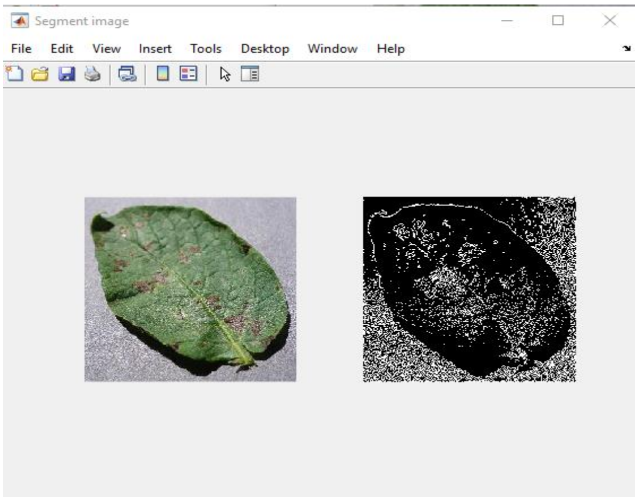

Fig 3. Segmentation.

After masking, pixels with zero values are discarded. Following the masking In the masking process, the values in the H and S planes are used to identify the diseased portion of the blade, and the value "1" is assigned to that portion. The remaining areas are all set to "0." The result is a binary image containing only them and zeroes. The diseased leaf area can then be removed

1.3.1 Threshold segmentation:
The image is segmented using equivalent segmentation based on the image's intensity or grey scale. This simple yet effective threshold-dependent approach for segregating images based on geographic images. On a dim or dark backdrop with light artifacts, this method is widely used. To segment image pixels into multiple categories and separate the object from the background, the threshold algorithm chooses a suitable threshold T.

A binary image clearly indicates that the image contains both zero and one values. The binary image is then multiplied by the RGB image's original value. This removes the leaf's infected portion. The knife mask and the resulting damaged area mask were used for further study. After the processing step, multiply the "damaged" area mask by adjusting the image RGB got. Since the mask only includes 1 and 0, the diseased part of the blade in the mask has the value of 1. When this image is multiplied by an RGB image, only the diseased aspect is shown.

1.4 Feature extraction (GLCM):
Functions are derived by reducing the amount of resources required to represent large amounts of data. The extracted functions should contain relevant information from the input data so that the necessary tasks can be completed using this simplified representation rather than the entire initial data. Quantifying the site's structural material is a useful method for explaining it. Smoothness, rawness, and regularity metrics are all properties of texture descriptors.

This study employs statistical methods for explaining texture. The grey level co-occurrence is used to evaluate the leaf image matrix in this process. The GLCM matrix is a matrix that is generated from an image of a specific picture I. This matrix produces a GLCM by deciding that a pixel of the grey value is displayed in the frequency next to the pixel of the cooler j. In every I j) feature of GLCM, the number of times the pixel level with the I is shown near the pixel with the j number is indicated. GLCM reduces the image to 8 grey levels, while I am a powerful image. GLCM value can be used to erase textures.

1.5 Classification Techniques:
Neural networks are used to carry out the classification process. The backscatter method is considered in the supervised learning phase. In most cases, a feed-forward propagation neural network has three layers: input, hidden layer, and output layer. The data will be used in the training of the neural network. Using neural networks, the algorithm determines two types of disease. Wilt of Fusarium and Berry Place Berry spot disease is a fungus that affects pepper plants. Plants with this particular type of disease may be fertilized to help solve the problem. Fertilizers like Pseudomonas can be used to feed such plants. Rapid redness is caused by a deficiency in the minerals nitrogen, magnesium, and potassium.

As a result, the device recognizes the disease type and, if the disease is detected, determines the addition of minerals to specific plants. The results of the tests are shown in the table below. The classification process is done by adopting Deep learning model. Back propagation method is considered under the supervised learning mechanism. Feed-forward propagation neural networks typically consist of three layers: an input layer, a hidden layer, and an output layer. Neural networks need to be trained using the available data. The structure of a convolution neural network mainly contains an input layer, a convolution layer, a pooling layer, a fully connected layer, an activation function, and usually a rectified unit (ReLU) layer. The number of layers using that arrangement and the introduction of other image processing devices vary from architecture to architecture determining its specificity.

1.5.1 GoogleNet-The GoogleNet architecture contains 27 pooling layers at a depth of 22 layers. A total of 9 starting modules stay in the linear. Both sides of the starting module are connected to the global average pooling layer. There are 4 million parameters across GoogleNet.

1.5.2 AlexNet-With advances in hardware, CNN architectures get bigger. AlexNet consists of 5 convolution layers, 3 maxpooling layers, 2 regularization layers, 2 fully connected layers and 1 softmax layer. Each convolution layer consists of a convolution filter and a nonlinear activation function ReLU. The pooling layer is used to implement max pooling. Since fully connected layers exist, the input size is fixed. The AlexNet has 60 million parameters overall.

Table 1. Comparison result of different deep learning architecture with existing technique

	Deep Learning Architecture	Accuracy
Proposed techniques	Alex Net	98.17
	Google Net	99.10
Existing work	KNN algorithm	94.0

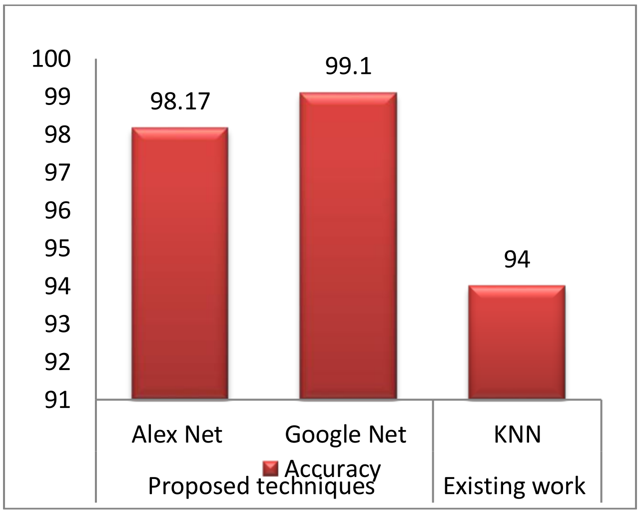

Fig 4. Showing the comparison performance of proposed model with existing.

Fig 2 comparison result of different deep learning architecture with existing technique Fig 4 showing the comparison performance of proposed model with existing techniques the proposed model compare with the other deep learning model, after the training and testing process AlexNet and GoogleNet model, the GoogleNet model get 99.10 the higher accuracy as compare to AlexNet model , GoogleNet model showing higher accuracy if we compare with the existing model.

IV. CONCLUSION

Image processing algorithms for finding disease detection and identification are being proposed. The leaves of the plant are used as a set of leaves when detecting leaf diseases. This algorithm produces better results, and with the help of this algorithm it is possible to distinguish between healthy and harmful plants. This image analysis technology can extract healthy plants from growing farms, improve productivity and ensure the quality of pepper plants as well. This algorithm helps determine the presence of a disease by observing the visual symptoms found on the leaves of the plant. A picture processing algorithm is proposed for detecting and recognising diseases. The leaves of pepper plants are used to identify leaf diseases. With the help of the algorithm, the algorithm can differentiate between healthy and unhealthy plants, resulting in better performance. This image analysis technology can be used to extract healthy pepper plants from farms, thereby increasing pepper fruit production and ensuring pepper plant quality.

This algorithm **observes** the visual symptoms of plant leaves and assists in diagnosing the disease. We propose image processing algorithms for disease detection and identification. The leaves of a plant are considered as a set of leaves when they detect leaf disease. The algorithm produces better results and with the help of this algorithm can distinguish between healthy and unhealthy plants. This image analysis technique can be used to extract good healthy plants on farms, increase productivity and guarantee the quality of peppers and plants. This algorithm helps determine the presence of a disease by observing the visual symptoms found on the leaves of the plant.

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