A Detailed Review on Recognition of Plant Disease Using Intelligent Image Retrieval Techniques

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Abstract
Today, crops face many characteristics/diseases. Insect damage is one of the main characteristics/diseases. Insecticides are not always effective because they can be toxic to some birds. It will also disrupt the natural food chain for animals. A common practice of plant scientists is to visually assess plant damage (leaves, stems) due to disease based on the percentage of disease. Plants suffer from various diseases at any stage of their development. For farmers and agricultural professionals, disease management is a critical issue that requires immediate attention. It requires urgent diagnosis and preventive measures to maintain quality and minimize losses. Many researchers have provided plant disease detection techniques to support rapid disease diagnosis. In this review paper, we mainly focus on artificial intelligence (AI) technology, image processing technology (IP), deep learning technology (DL), vector machine (SVM) technology, the network Convergent neuronal (CNN) content Detailed description of the identification of different types of diseases in tomato and potato plants based on image retrieval technology (CBIR). It also includes the various types of diseases that typically exist in tomato and potato. Content-based Image Retrieval (CBIR) technologies should be used as a supplementary tool to enhance search accuracy by encouraging you to access collections of extra knowledge so that it can be useful. CBIR systems mainly use colour, form, and texture as core features, such that they work on the first level of the lowest level. This is the most sophisticated methods used to diagnose diseases of tomato plants.

Keywords:
Artificial Intelligence, Deep learning, Tomato leaf disease, Potato leaf disease, Content-based image retrieval (CBIR)

I. Introduction

Agriculture is the backbone of the economy of India. The large-scale commercialisation of agriculture has had a very negative effect on our climate. The use of chemical pesticides creates a substantial build-up of chemicals in our atmosphere, soil, water, food, livestock, and also in our own bodies. Artificial fertilisers have a short-term effect on production but have a long-term detrimental impact on the environment. After leaching and loss, the chemical fertiliser will remain in the soil for many years and will pollute the groundwater. Another negative effect of this development is its effect on the situation of rural populations around the world. Despite the so-called rise in production, the plight of farmers in nearly every country in the world is deteriorating. It's the root of organic farming. Natural farming can solve all these issues. The main practices in organic farming rely on fertilisation and control of pests.

Potato is one of the most significant food crops. The diseases causing substantial yield loss in potato are Phytophthora infestans(late blight) and Alternaria solani (early blight). Early detection of these diseases can allow to take preventive measures and mitigate economic and production losses. Over the last decades, the most practiced approach for detection and identification of plant diseases is naked eye observation by experts. But in many cases, this approach proves unfeasible due to the excessive processing time and unavailability of experts at farms located in the remote areas [1]. Hence, the introduction of image analysis tools turns out to be an effective method for continuous monitoring of plant health status and early detection of plant diseases. As diseases leave some visible symptoms on the plants, particular on leaves, disease detection can be performed by imaging analysis of those visible patterns on leaves. Thus imaging technique combined with machine learning offers a solution to the issue of agricultural productivity and ensures food security. [16-20]

Detection of plant diseases by physically analysing the signs of plant leaves easily brings difficulty. Due to this difficulty and the vast number of crops grown and plant pathology issues that occur, even qualified agricultural specialists and plant pathologists will sometimes struggle to identify particular diseases, leading to inaccurate findings and responses to programme issues. An automated device designed to

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help diagnose plant diseases by the presence and visual signs of plants can be of great benefit to agricultural production enthusiasts. This will prove to be a valuable strategy for farmers and will be recalled at the right time before the disease spreads over a wide regio.[17-22].

Potato is one of the most important crops for food. The diseases that have induced a sharp decline in potato production are Phytophthora phytophthora (downy mildew) and Streptomyces solani (downy mildew). Early identification of these diseases can take preventive measures to minimise economic and production losses. Over the past decades, visual evaluation by professionals has been the most realistic way of detecting and distinguishing plant diseases. In certain cases, however, this approach has proved to be inefficient due to the long processing period and inaccessibility of agricultural experts in remote areas[1]. The implementation of image processing software has also proved to be an important approach for the continuous monitoring of plant health and early identification of plant diseases. If the disease leaves noticeable signs on the plant, particularly on the leaves, the disease can be identified by imaging and examining these recognisable patterns on the leaves. Imaging technology combined with machine learning also offers a solution to the issue of agricultural production and assures food security.[25,28,29]

Tomato is one of the world's most valuable crops. According to the Food and Agriculture Organisation of the United Nations, the production of world tomatoes amounted to approximately 170,750 kilotons in 2014[1]. Plant diseases have always been a thorny problem in agricultural production and one of the key factors restricting sustainable agricultural growth. Tomato is a popular vegetable and a major economic crop in China. It is extensively planted in different areas and occupies an area of around 700 million square meters. Tomato disease is also caused by different environmental factors[2].

Detection of plant diseases is always a daunting task. The major sources of infection are fungi, bacteria and viruses in plants. These infections can affect any part of the plant, such as leaves, stems , and roots.[28-30]. In order to obtain better quality and profitable crops, farmers recognise the right goods by measuring and regulating the required specifications for temperature, light, and humidity[3]. In addition, due to population growth, climate change, and political instability, agriculture has begun to find new ways to expand food production. This encourages researchers to look for new, resource-rich, and efficient innovations that can help improve agricultural productivity. However, difficulties exist, such as early identification of pathogens in plants and plant problems. It is difficult to continually detect the kinds of diseases in the leaves of plants with the naked eye. The electronic system of specialists would also be very helpful, and will aid in the timely diagnosis of diseases. Alternative electronic approaches for quick and non-invasive detection of tomato diseases have been investigated in recent years.[31]

There are the various disease that generally occurs in plants Fig. 1;

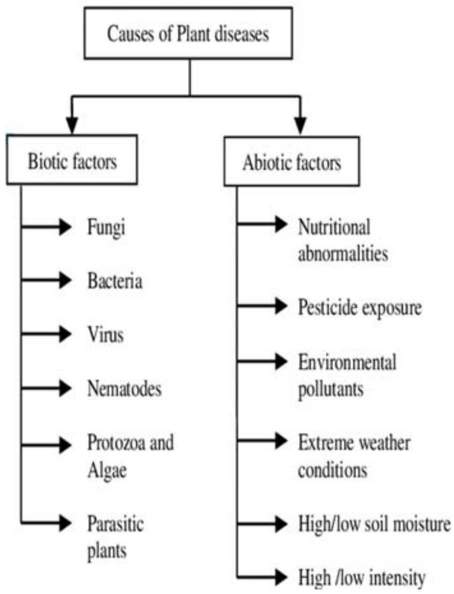

Fig. 1 Various causes of disease in plants [2]

Precision cultivation can be used to control certain pests and diseases. The use of these chemical or expensive processes can be minimised by using precise cultures. In the field of precision agriculture, sensor technology, computer processing, remote sensing processing, robotics, and other information technologies are used. For precision agricultural applications (such as spraying only infected areas), it is important to recognise places where plant diseases are occurring and spread. Operators, static stations, sensor networks, drones, and mobile robots are used for the monitoring of precision agriculture. The only drawback of these methods is that they can not find specialists in the area. In order to conduct precision breeding, these instruments must be able to analyse and draw lessons from the data gathered, either as field or greenhouse experts. For photographs obtained with remote sensing devices or field instruments, image processing has been commonly used in the area of precision agriculture. [2, 5, 8]

Various types of disease are classified by the following fig. 2;

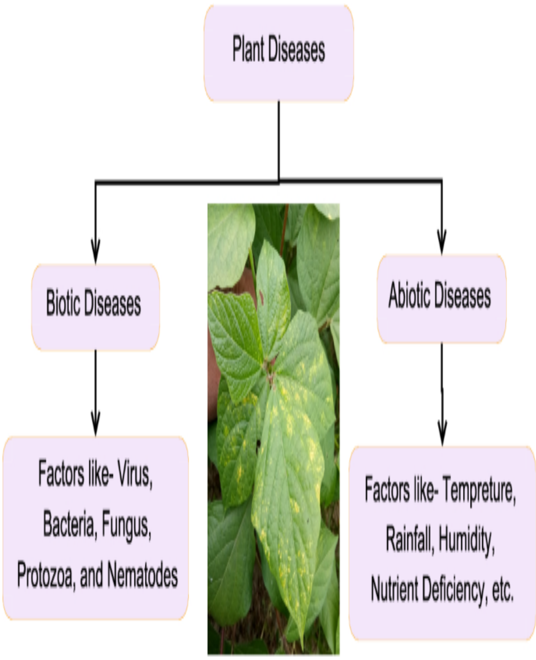

Fig. 2 Different types of disease in plants [6]

Picture analysis has been widely used in the literature of agriculture. For example, image processing is used for weed identification and fruit classification, plant disease identification, phenotypic quantification and classification, and plant disease symptoms analysis[7]. Deep learning has recently been used for detection [8]. Mohanty et al. In their study, deep learning was used to identify leaf diseases in different plants[8]. Deep learning is the most popular form of machine learning using hidden layers of artificial neural networks (ANNs). Classification tasks using semantic characteristics were performed prior to the advent of deep learning patterns.

Deep learning (DL) methods are a branch of machine learning (ML) and were implemented in 1943[1] when threshold logic was developed to create computational models that closely mimic human biological pathways. This area of study continues to grow. Its history can be divided into two phases, from 1943 to 2006 and from 2012 to the present.

Farmers can not carry out periodic surveys in fields longer than miles at a time to track each plant intensely. In rural areas, too, the shortage of skilled farmers has always been the issue of detecting diseases at the right time. Many developed countries have opened plant clinics for farmers, where they can learn about different diseases and insects. In addition, plant pathologists will identify diseases from samples collected from farmers in these clinics. In addition, agricultural extension officials have also toured the property. Nowadays, fuzzy logic is used to identify plants as diseased or stable plants. If the disease is observed, software (such as fuzzy inference systems) can also be used for classification purposes.

Many researchers have used image characteristics (such as colour, form, texture, and combinations) to build CBIR systems for various applications. Expand the CBIR method utilising colour functions such as the RGB colour histogram, the GLCM colour histogram, and the K-Means colour histogram. Image texture features, such as local binary pattern (LBP) and LBP variance, can be used to build CBIR systems. Researchers use the modulated discrete transform cosine (SADCT) and vector scale function (SIFT) for Canny Acne Detection (CED) as shape characteristics for the design of CBIR systems. The CBIR method, which uses a mixture of colours, shapes, and textures, is very successful. Any Gabor colour moments and philtres, autocorrelation maps, BDIP and BVLC moments, Gabor colour moments and texture details, wave, and pattern histogram moments, pattern and geometry moments, grey coexistence matrix and Zernike moments, HSV colour moments The mix. Transform description, colour histogram, colour correlation map, grey co-occurence matrix, and Tamura-Hu pair, colour pair and LBP, HSV colour histogram, and co-occurence matrix [7].

II. Different types of tomato disease

Tomato (Solanum lycopersicum) can be grown in almost any well-drained soil. An adequate supply of organic products can improve yields and reduce production issues. Tomatoes and associated vegetables (such as tomatoes, peppers, and eggplants) should not be planted several times in the same soil in three years. Ideally, any cover or crop previous to the tomato should be a part of the grass family. Corn is a healthy tomato crop, supplying a significant amount of organic matter and not allowing the growth of pathogenic species that infect tomatoes. The use of approved seeds and plants is advised and can be done whenever possible.[39]

There are many types of diseases in tomatoes, some of the most serious and common diseases will be explained below.

1. Bacterial wilt

Bacterial soil or bacterial disease is a severe illness caused by Ralstonia solanacearum (formerly Pseudomonas solanacearum). This type of bacteria can live in the soil for a long time, enter the roots of plants by transplantation, cultivation, or wounds caused by insects and enter the roots by natural wounds. Hot temperatures and humidity contribute to the growth of the disease. Bacteria reproduce quickly in the aquatic plant tubes and fill with mucus. This causes the plant to wilt easily, although the leaves remain green. If the infected stem is transversely sliced, it may look brown and a reduction of yellowish exudate can be seen [8-12] fig. 3.

Fig. 3 Bacterial wilt

2. Early Blight

The disease is caused by Streptomyces tomato and Agrobacterium solanum and was initially seen as small brown lesions on plants, often on older leaves. The spots are widened and the concentric circles can be seen in the middle of the outbreak, suggestive of the bullfighting. The tissue around the stains will turn yellow. If high temperatures and high humidity exist at this time, most leaves will die. Stem diseases are similar to those of trees. If they are close to the soil line (collar), they can occasionally pinch the vine. In the forearm, the lesions attain a large amount, usually occupying nearly the whole forearm. Concentric rings are found in the fruit as well. Infected fruits also break apart. The disease lives in infected soil waste, seeds, volunteer tomato plants, and other Solanaceae hosts (e.g. Irish potatoes, eggplants, and black nightshades) [8-12], fig. 4.

Fig. 4 Early Blight

3. Late blight

Stunting is a potentially severe disease caused by Phytophthora in potatoes and tomatoes. Delay is highly harmful in cold, humid climates. The disease is infecting all areas of the vine. The sick spots on the young leaves are tiny and show as dull, water-soaked spots. These leaf spots propagate rapidly, and white mould appears along the edges of the infected area on the underside of the leaf. Total defoliation (darking and shrinking of leaves and stems) may occur within 14 days after the first symptoms begin. Infected tomato fruits have a glossy, black, or olive look that can cover a wide area. Fungal spores disperse between plants and gardens under the influence of rain and wind. Daytime temperatures above 70 degrees Celsius and high humidity are well matched to infection [9,20,22].

4. Septoria Leaf Spot

This debilitating disease of tomato leaves, roots, and roots (the fruit is not infected) is caused by Septoria lycopersici fungus. Typically, as the plant starts to bear fruit, the fungus occurs on the lower leaves near the bottom. Many tiny circular spots occur on older leaves, surrounded by dark beige-centered margins. Tiny black spots occur in the middle of the spots that are spore-producing artifacts. The very marked leaves turn yellow and die and fall off the vine. The fungus is more aggressive when the temperature is between 68 and 77 ° F, the humidity is heavy and the rain or good irrigation moisturises the plants. Falling leaves hinder the growth of the plant, reduce the size and consistency of the fruit, and expose the fruit to burning (see below). This fungus does not propagate from the soil but does survive winter crop residues, plant destruction, and some tomato-associated wild tomatoes [10,40], fig. 5.

Fig. 5 Septoria Leaf Spot

5. Leaf Mold

The Passalora fulva fungus causes leaf mould. This effect was first observed in older leaves near the ground with poor airflow and high humidity. The first signs are a bright green or yellowish spot on the upper surface of the leaves, which expands and becomes noticeable in yellow. In wet conditions, the areas on the lower surface of the leaves are hidden by the velvety and grey growth of the fungus spores. When the infection is severe, the spots merge and the leaves die. Fungi will also infect roots, flowers, and fruits. Ripe green fruits may have black leather rot on the tip of the stem. [41]

Fungi live in crop residues and dirt. Spores are dispersed by rain, wind, or instruments. The seeds may have been contaminated. Fungi rely on high relative humidity and high temperature for the propagation of disease[10, 11], fig.6.

Fig. 6 Leaf Mold

6. Bacterial Spot

The disease is caused by the bacterium Xanthomonas, which infects green tomatoes instead of red tomatoes. The pepper is being targeted. The illness is more prevalent during the rainy season. Plant damage includes leaf and fruit spots, resulting in reduced yields, defoliation, and sunburn. Symptoms include several small, angular to circular, water-soaked spots on the leaves and slightly elevated spots on the fruit. The spots in the leaf may have a yellow halo. The middle sometimes dries up and calls out [43], fig. 7.

Fig. 7 Bacterial Spot

7. Tomato Pith Necrosis

Tomato necrosis is typically an early illness that occurs in greenhouses and in high-yield tomato production. When it rains in the spring, however, tomato necrosis will kill tomatoes and occasionally bell peppers in the home gardens. Lung necrosis is caused by a number of soil-borne Pseudomonas, including Pseudomonas crinkle and Carnosus carnosus. These bacteria are called weak pathogens and can invade rapidly growing tomato plants in wet, cold, and humid environments [12], fig. 8.

Fig. 8 Tomato Pith Necrosis

8. Anthracnose

Carcinogenicity of tomatoes is caused by the fungus Colletotrichum coccoides, which is mainly a pathogen of tomatoes. When the fruit ripens, the signs first appear as small circular jagged patches and then eventually darken. When each region of infection progresses, the lesions will begin to spread over time. In hot, humid, and humid climates (with or without rain) the fungus develops salmon-colored spores that arise from the black fungal substance in the centre of the field. These spores are released by the splashing of water [43], fig. 9.

Fig. 9 Anthracnose

9. Southern Blight

Athelia rolfsii infection (synonymous with Sclerotium rolfsii) causes the disease. The first symptom is bent palms, which suggest other vision problems. A brown dry rot may occur on the soil line on the base. White fungus growth can be seen with large and small white sclerotia of mustard seed. Stem lesions grow quickly, spread around the base, causing abrupt and lasting wilting of all antennas. Typically the lesion is concealed by a white fungus. Fungi will also infect fruit where they touch the earth. Fungi have been able to live in soil and plant litter for many years. It is influenced by humidity and high-temperature conditions[14], fig. 10.

Fig. 10 Southern Blight

10. Growth Cracks

When the environmental conditions (heavy rain or irrigation after a drought) promote fast growth during the ripening season, the tomatoes can burst. Any cracks can be deep, allowing rotting species to invade the fruit and cause the fruit to rot [14], fig, 11.

Fig. 11 Growth Cracks

III. Different types of disease in potato plants

1. Black scurf & Rhizoctonia canker

Rhizobium infection causes the death of potato plants. Potato tubers covered with fungal fruit bodies. Potato tubers covered with fungal fruit bodies

Symptom

The surface of the tuber is smooth, irregularly coloured, black, or dark brown fungal; the tuber may be deformed; the reddish-brown to black depression of the bean sprouts; the lesions may constrict the main stem, causing the leaves to curl and turn grey, fig. 12.

Fig. 12 Black scurf & Rhizoctonia canker

2. Potato Early Blight

Symptoms – lesions with black edges can create concentric circles of raised and sunk tissue on leaves and stems; the lesions are initially circular but become angular; the leaves are necrotic but still attached to the plant; the tubers are dark and dry. Lesions have a look like leather or cork with a watery yellowish-green tip.

Cause-Fungus

Note-The emergence of diseases is conducive to the cycle of wet and dry conditions, as well as periods of high humidity and wet leaves, fig. 13.

Fig. 13 Potato Early Blight

3. Flea beetles

Symptoms: Small holes or pits on the leaves give the leaves a characteristic "diffuse" appearance; young plants and seedlings are particularly sensitive; plant growth may be reduced; if the damage is severe, the plant may be killed; The pest causing damage is a small black beetle (1.5-3.0 mm) that jumps when disturbed; the beetle usually has a shiny appearance.

Cause: Insects

Comment: Young plants are more susceptible to damage by flea beetles than older plants; older plants can tolerate infestation; flea beetles may overwinter in neighboring weed species, plant debris, or soil; insects can experience it within a year. The second or third generation, fig .14.

Fig. 14 Flea beetles

4. Potato Late Blight

Symptoms: In wet conditions, at the edge of the lesion on the underside of the leaf, irregularly developed brown lesions scatter across the leaf and white sticky spores develop on the ground. When it is dry, the lesion turns dry and dark brown and the tissue falls. Dark green to brown lesions on water-soaked stems often display a distinctive white spore formation; later, the leaves and petioles rot entirely through infection; badly infected plants will have a clear, mildly sweet odour; rough red-brown tuber lesions expand to tissue in the middle of a few centimetres; the presence of the lesion can be mildly bloated and sometimes contribute to secondary lesions.

Cause: Oomycete

Comment: Diseases can remain in the soil for months or even years; warm and cool temperatures favour the growth of disease; the major cause of disease transmission is tuber infection, fig. 15.

Fig. 15 Potato Late Blight

5. Potato leaf roll

Fig. 16 Potato leaf roll

Symptoms: The young leaves are twisted, yellow, or pink. The lower leaves are leathery in texture and roll upward; there may be a necrotic network in the tissue of the tuber of the blood vessel; the plant has vertical growth and growth may be blocked.

Cause: Virus

Comment: Spread by several aphids; infected tubers and volunteer potato plants are a source of inoculation for the virus, fig. 16.

IV. Different techniques for detection of tomato disease

1. Deep Learning with Convolution Neural Network (CNN)

Much like LeChun, and so on. Deep learning is a way of reflecting learning in her research[12]. Here, representation learning means that the algorithm can find the best way to replicate the results. This representation is discovered by the algorithm by optimization rather than semantic characteristics. No practical engineering is expected during this learning process. All the products are sold immediately. Mathematically, deep learning is an artificial neural network with unknown layers. Fig 17a displays a neural network of two hidden layers, and Figure 1b displays a schematic diagram of the perceptron. Perceptrons have been inspired by live neuronal cells. -- sensor has several inputs (only 5 inputs are seen in Fig 17b) and trigger functions. (1) The mathematical formula for the neuron is given. The activation function makes the neuron's response non-linear, while the network without the activation function is a linear combination of inputs. There are several roles of activation in the literature, such as type S, tanh, and ReLU. ReLU is one of the most commonly used stimulus functions and can be trained more quickly [9].

The weights for each perceptron are calibrated at the beginning of the preparation. The variance from the Gaussian sample can be initialised. At each point of the iteration, all training data will be distributed across the network. As supervised instruction, the deficit between the real field and the grid output will be determined. Loss is the reference to the algorithm for optimization. The optimization algorithm updates the weights on the basis of this failure. The stochastic gradient descent (SGD) algorithm is one of the most commonly used optimization algorithms. In brief, SGD minimises repeated loss on the basis of gradient update processes. There is a special network architecture called the Convolutionary Neural Network (CNN) for images such as relatively large, high-dimensional imagery. CNN was used for the first time to find handwritten numbers in documents[13]. CNN consists of a coherent layer, a focus layer, an activation layer, an escape layer, and a totally connected layer. The adhesive layer stores the influence of the philtre or core in combination with the previous layer. These philtres or cores are composed of weights and biases. The aim of the optimization feature is to build certain cores that reflect error-free results. The fused layer is used for downsampling to reduce the size of the neurons and to minimise over-placement. The most commonly played form of billiards is the one with the highest volume that earns the most value in the pool frame. The degree of trigger mode is used to apply non-linearity to the network. The normal stimulus is called the ReLU. The abandonment layer is used to prevent overlaying. The packet loss layer inadvertently switches off the neurons on the network. The completely associated degree is used to measure the chance or ranking for the class. The input of the classifier may be the output of the completely connected layer.

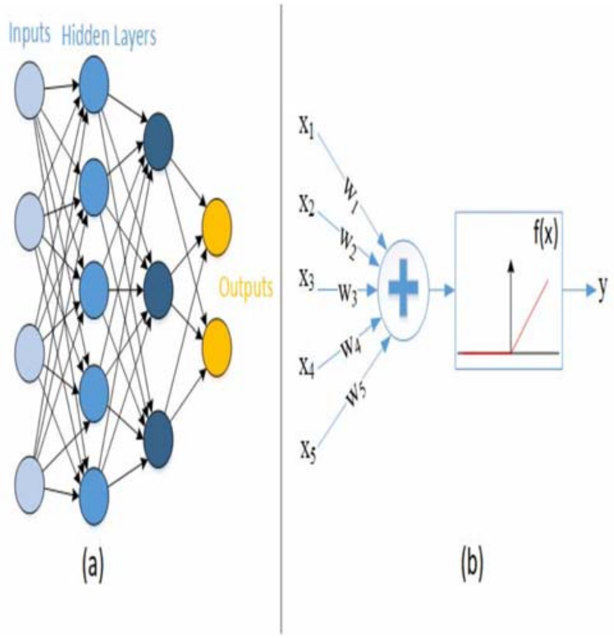

Fig. 17 a) Deep neural network, b) Schematic representation of a perceptron.

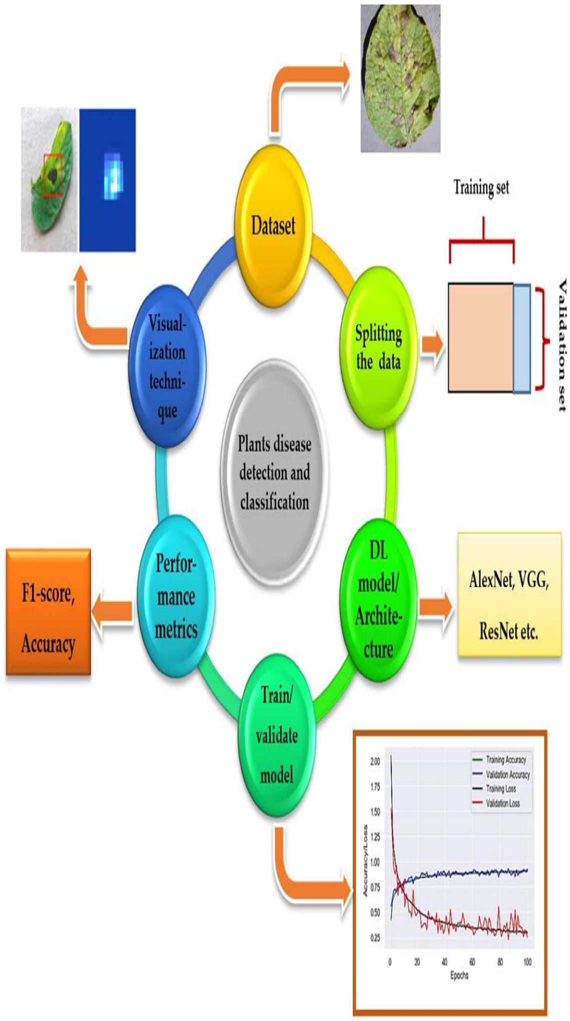

Fig. 18 DL deployment flowchart

Figure 18 DL deployment flowchart: First, collect the dataset [25-27] and then split it into two parts, usually divided into 80 percent training and 20 percent validation. After that, develop the DL model from scratch or use transfer learning strategies to get the training/validation graph to demonstrate the value of the model. Then, output metrics are used to classify the image (specific categories of plant diseases) and eventually, visualisation/mapping techniques are used to detect / locate / classify pictures.

The dominant neural network is a type of deep neural network capable of processing multidimensional data. CNN's aim is to simplify the picture to a conveniently accessible format without sacrificing the functionality required to make accurate predictions. CNN has a number of platforms, such as AlexNet, GoogLeNet, VGGNet, etc. Its production has given rise to a great deal of interest among researchers in various fields of computer science[9-12]. It has been used in agriculture to identify plant diseases. As seen in Figure 6, the CNN model contains an input layer, a coherent layer, a focus layer, a totally bonded layer, and an output layer. Images are used as inputs to correctly identify diseases in plants. Cohesive layers are used to remove the characteristics of the images. The concentration degree measures the characteristic values of the exported characteristics. Depending on the sensitivity of the file, you can add more convergence and blend for more detail. The completely connected layer takes the output of the previous level and transforms it to a single vector that can be used as input to the next level. Finally, the degree of development classifies plant diseases, fig 19.

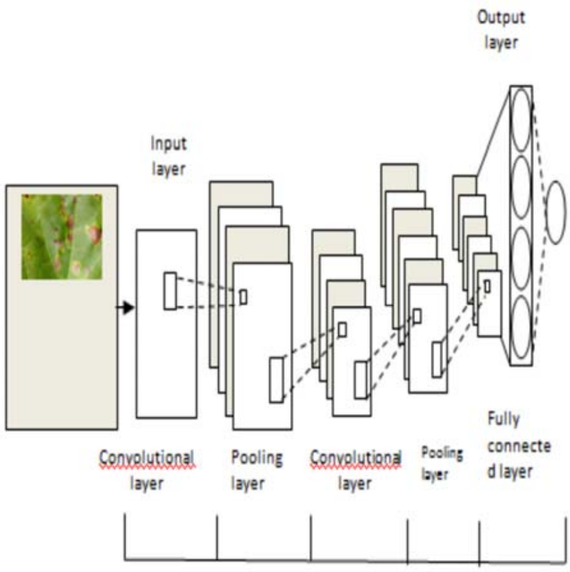

Fig. 19 Plant disease classification through CNN [9]

2. Support Vector Machine (SVM)

The support vector machine (SVM) is a learning algorithm focused on reducing structural risk that is often used for classification and regression problems. It is designed to optimise the classification cap so as to distinguish the two divisions as far as possible. As seen in Figure 13, for the purpose of collecting acceptable data points, SVM has been extended to this region and is referred to as a hyperplane. The carrier shall mark neighbouring points on the aircraft on both sides of the aircraft. In order to distinguish these vectors, a fixed margin should be used, which should be the largest by which the SVM can be efficiently equipped, fig 20.

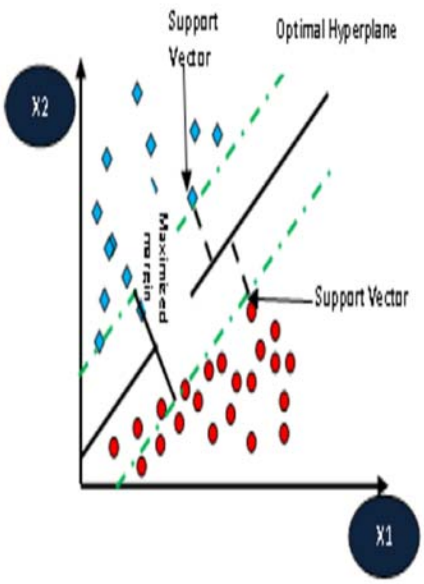

Fig. 20 Disease recognition and classification using SVM

3. Artificial Intelligence

Data mining today is a efficient and versatile tool that can be used to forecast plant diseases. Thus, by integrating data mining principles with image analysis, we can quickly determine which crops are contaminated, distinguish diseases according to different problems and colours caused by diseases, and propose alternative therapies depending on the magnitude of diseases.

4. Content Based Image Retrieval Technique

CBIR infrastructure functions independently from conventional text library systems. Import images stored in a cluster and then use the features of these images to compare them. The image functionality will be exported automatically [4], fig. 21.

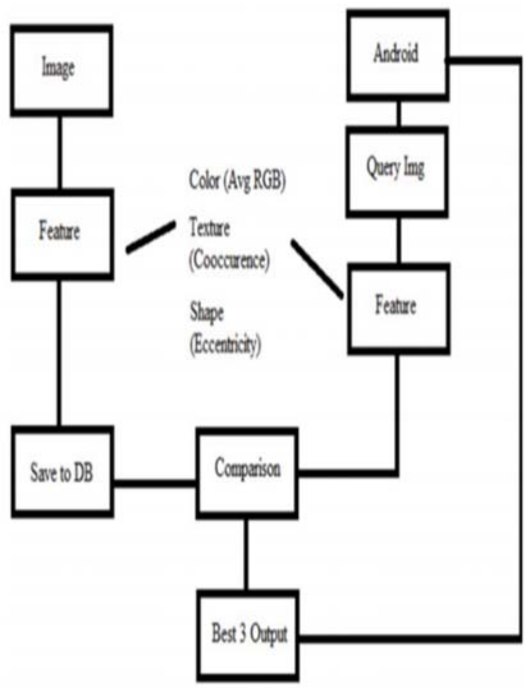

Fig. 21 CBIR based system architecture

CBIR systems mainly use colour, form, and texture as core features, such that they work on the first level of the lowest level. Traditional systems allow queries from users taking data like images, while some systems have additional choices for users, such as palette or sketch entry. In the next step, the system compares the query image to the stored images and fits them correctly with their attribute values, and these images will be displayed to the user. The key categories of image searches are discussed below.

A. Colour Retrieval

The method of extracting details from a color-based picture has been clarified in a variety of ways. However, several of the approaches are variations of the general principle of colour recovery[25]. As the images are used for contrast, they are first analysed and then the colour histogram is taken from the image, indicating the colour ratio of and pixel in the image. The histogram[6] colour extracted from the image is contained in the database. The user will determine the colour ratio of the input picture during the quest while determining the colour histogram. Consider an image whose colour histogram is very similar to the image in the question. Swain and Ballard were the first to develop the histogram mapping method now commonly used. The advancement of the related technologies allows the use of CBIR technologies in more complex systems. The latest Swan and Ballard enhancement strategies include composite colour histograms and area-based colour queries. The effect of this technique is an improvement on the prior art.

B. Texture Retrieval

Image similarities may also be based on shape, although they can sound futile. Texture equality can be used to differentiate between the colours and the areas of the graphic[26]. The texture similarity is obtained by comparing the query values and the image contained in the database. Consider comparing the dynamic brightness parameters of two pixel pairs of images. Calculate the value on the basis of the scale, contrast, position and periodicity of the texture analysis. Gabor philtres and fractals are another tool for evaluating image textures. Complete a texture contrast by uploading a query image or choosing textures from the palette. The device will then take into account images whose texture dimensions complement the query image very well.

C. Shape Retrieval

The third technique is to use type retrieval to extract information from the file. The basic prerequisite for the recovery of image characteristics is by formatting, which is the basic stage of formatting technology. In comparison to texture, the form is a well-defined process. There is a lot of evidence that certain objects in existence are mainly identified by their forms. Many characteristics of the shape of the object (regardless of the size) [28-31] are processed for each image contained in the database. The question is addressed by manipulating the corresponding properties of the query image and collecting certain images whose capabilities closely equal the query image. Two essential form characteristics are widely used, such as universal characteristics (such as aspect ratio), invariant rounding, and local moments and characteristics (such as the set of continuous boundary line segments).

V. Conclusion & Future Scope

In this evaluation paper, we focus primarily on artificial intelligence (AI) technology, image processing (IP) technology, deep learning (DL) technology, vector machine technology (SVM), convergent neural network (CNN), content The detailed description of the identification of different types of diseases in tomato plants based on image retrieval technology (CBIR). It also covers the various types of diseases commonly produced in tomato plants.

The last work has been analyzed and described in dots. It can be concluded that among the technologies used in the existing work, the concept of deep learning through the CNN method has achieved the highest accuracy.

This analysis describes how CNN DL, AI, SVM, and CBIR tools are used to diagnose tomato disease. In addition, several imaging/map methods are illustrated for the diagnosis of disease symptoms. While much progress has been made in the last three to four years, there are still some holes in the research listed below:

1. In most of the studies (as mentioned in the previous sections), the dataset of PlantVillage is used to test the accuracy and efficiency of each DL model/architecture. While this dataset contains photos of several diseases of plant species, it has a simple/light history. However, the real world must be taken into account in the actual situation.
2. Superspectral / multispectral imagery is an new technique that has been used in many areas of science (as defined in Section 3). Therefore, particularly though signs are not apparent, sophisticated DL software must be used to diagnose plant diseases.
3. More analytical techniques for visualising plant disease spots should be implemented as they will prevent excessive use of fungicides / pesticides / herbicides, thus saving costs.
4. Over time, the magnitude of plant diseases will change. It is also important to improve/modify the DL model so that it can be identified and categorised during the onset period of the disease.
5. The DL model/architecture must be effective under multiple lighting environments, so that the data collection does not only display the current world, but must also include photographs taken under natural conditions.
6. Thorough research is required to explain the factors influencing plant diseases, such as the form and scale of the data collection, the learning rate, the illumination, and so on.

Contributions

Both the authors have contributed in the manuscript preparation. Data collection is done by Gulbir Singh and Kuldeep Kumar Yogi. The manuscript is drafted by Gulbir Singh.

Conflict of interest

The authors declare that there is no conflict of interest.

Ethics approval

This manuscript doesn't involve any kind of research in human and animal, the ethical approval not applicable.

Consent to participate

Both the authors consented to participate in the preparation of this manuscript.

Consent to publish

Both the authors consented to publish this manuscript, so its not applicable.

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