Chapter 1

CHAPTER 1

INTRODUCTION

This chapter discusses the history of farming in India, the various leaf diseases that can affect plants, causes of these disorders and the roles they play, the various pests that can cause them, and the methods that can be used to get rid of them, as well as the uses of digital image processing and AI models in agriculture. Moreover, the study's background, goals, and contributions to pesticide recommendations and the development of new technologies for detecting plant diseases and pests are highlighted.

1.1 BACKGROUND

Over 2 million species of plants, animals and fungi have been identified on Earth, with plants playing a particularly important role in human evolution and survival. Plants are indeed a universally accessible resource for human well-being. Even the smallest of plants may improve the quality of life by providing humans with a window into the natural world.

Plants are incredibly valuable because they form the basis of the food supply chain and are the source of many medications. Plants have continually valued environmental protection. It appears that after many revolutionary advances in plant biology, a vast number of plant species have been discovered, labelled, or utilized. Many documented cases of plant species have yet to be identified. Ethnologists are starting to combine regions all over the world to find new medicinal and agricultural materials. To better understand the need for adaptable resource management, they study the major characteristics and associations of plant species across habitats. Scientists in the twenty-first century have been looking into how genomic diversity and more importantly, environmental resistance, can help with problems like mass feeding and disease prevention. The progress and output of the plant are severely hampered by the disease that has engulfed it.

Therefore, it is crucial to find forms and strategies to combat plant pathogens to maintain a sufficient supply of food for all life on Earth. It appears to be challenging to detect plant diseases and evaluate their severity. Human eye assessment appears to have been the primary method for determining the severity of disease until recently. These individuals consistently report crop field observations to allow for an expert's accurate estimation of disease. Because it requires constant manual inspection, it is expensive, time-consuming and inconvenient for large areas of plants.

The need for, and supply of, food is being rapidly affected by the ever-increasing human population. Under these circumstances, society as a whole must consider implementing cutting-edge tech to improve its capacity for early disease detection and rapid response. One of the most trustworthy and inexpensive ways to establish criteria for plant disease is through data mining and image processing analysis using AI models.

1.1.1 Agriculture in India

Planting essential crop production has been a part of agricultural production ever since the earliest days of civilization. In addition to being the backbone of the country's economy, agribusiness helps meet the rising demand for food. As the economy expanded, many new agriculturally related occupations emerged as well. In a broader sense, agriculture contributes to national economic growth and prosperity by creating opportunities in the private market and serving as the primary impetus for agricultural production economies. Industrial agriculture encompasses manufacturing, marketing, research and distribution of agricultural goods.

Producing food for human consumption is one of the many ways agriculture helps people (Bhattacharyay et al. 2020). Cultivation, biochemical usage, seed substitution and other agricultural process advancements have become long-term motivators. But its application would have progressed greatly over the past century. Compared to medieval times, modern agricultural practices have increased food harvest yields by a margin of several percentage points. About 70% of Indians rely on agriculture for their livelihood, and the country is rapidly becoming the world's seventh largest market due in large part to its rapidly expanding Gross-Domestic-Product (GDP) (Bharatkumar et al. 2023).

The agricultural sector in India is vital to the country's economy. Rice and wheat, along with fruits and vegetables, are a few examples of economically beneficial crops. About 17% of the country's GDP comes from agriculture and related industries like beekeeping, horticulture, logging, breeding, fisheries, and timber. In terms of agricultural output, India is currently ranked second. When it comes to the nation's economy and society as a whole, agricultural production is undoubtedly a top priority (Cariappa et al. 2021). India's total cultivated land area exceeds 210 million hectares (Rosa et al. 2021). Some of the most common fruits were the banana, mango, grapefruit, orange, apple, watermelon, guava, strawberry, pawpaw and pomegranate, while the most important crops included maize, rice, corn, sugarcane, wheat, peanuts, grains, cereal grains and sunflowers. Crops like spices, coffee, dragon fruit, tea, silk, vanilla, etc., are much more valuable from a business perspective.

1.1.2 Challenges in Agriculture

Changes in the rainy season, soil conditions, and environmental conditions all harm agricultural output (Shahzad et al. 2021). Diseases affecting these crops are a major reason for decreased agricultural output for the vast majority of the year. Accordingly, preventing or mitigating the effects of these diseases is of paramount importance. There are a wide variety of microorganisms that can cause plant infections, including viruses, bacteria, fungi and others (Li et al. 2021).

Both autotrophs (also called parasitic infections) and saprophytes (also called heterotrophs) can develop from these pathogens or disease factors. Parasites thrive on healthy cells, while saprophytes thrive on dead ones (Altinok et al. 2019; Harper and Krings 2021). In addition, there are universally present facultative. Reduced and less reliable harvests can be directly attributed to the prevalence of plant diseases. This is bad for the economy of the country. Diseases that reduce crop yields are proving difficult for farmers to control. So, the ability to accurately identify crop diseases has emerged as a critical need for agriculturalists. Recognizing diseases in crops across plant segments at an early stage of development is a challenging skill (Idoje et al. 2021). However, many of the diseases that attack different parts of plants can be recognized by the visual changes they cause.

Diagnosing plant diseases is an impressive and insightful skill in and of itself. Early civilizations had to rely on expert farmers and specialists to diagnose disease outbreaks, which was labour-intensive, time-consuming and expensive (Shaikh et al. 2022). Maintaining crop production, protecting the environment and beginning to reduce the use of toxic pesticides and sprays are all possible goals. Thus, it is of paramount importance to agricultural experts, researchers and investigators that automated disease identification, diagnosis, categorization and the suggestion of prevention strategies be developed. Therefore, making a correct diagnosis earlier and stopping the spread is the best way to ensure better production.

Therefore, it is imperative to utilize cutting-edge technology such as computer science, machine learning (ML) and computer imaging and processing to increase productivity and further contribute to the economic progress of the country (Sharma et al. 2020). Pathogens in agriculture and allied sectors can now have a visual representation due to these images. Observation and analysis of plant diseases, their impacts and visual criteria, as well as recorded photographs of plant parts, are helpful. The primary choices in recent decades have been to replicate, imitate, examine and represent these recorded images.

Optical image analysis, geographic and spectral analysis image processing, contrast adjustment and reconstruction methodologies are only some of the many fields that could benefit from their flexibility and ease of interpretation. It aims to automatically detect plant diseases using state-of-the-art equipment and techniques in conjunction with ML techniques. Potentially far-reaching implications for agriculture, horticulture, and national development may result from using ML and image processing algorithms to detect leaf diseases at an early stage (Javaid et al. 2023).

1.1.3 Leaf: A Vital Organ of a Plant

Botanical terms and plant anatomy are used to describe a leaf because it is often an organ of a vascular plant. As a plant characteristic, leaves are the most common example of foliage (Shtein et al. 2019). A leaf is a thin, flat shape that develops above ground and engages in photosynthesis. Many functions of plant leaves are the following:

- Food manufacturing relies on a photosynthesis system that includes respiration processes like the exchange of gases and air
- Safety for bloom buds and new plants
- Transpiration is an important part of the water cycle, but it also serves other functions
- Keep some food on hand for the sprouting stage

The leaves are the most vital component of a plant's framework and they are made of a malleable, non-rigid material. These entities on plant species were plain to see, therefore they can be studied and appraised with no additional testing required. To properly identify a leaf, one must consider its size, shape, colour and vein composition in addition to those of other leaves within and across taxonomic families (Long et al. 2023). Various exterior leaf parts are shown in Fig 1.1.

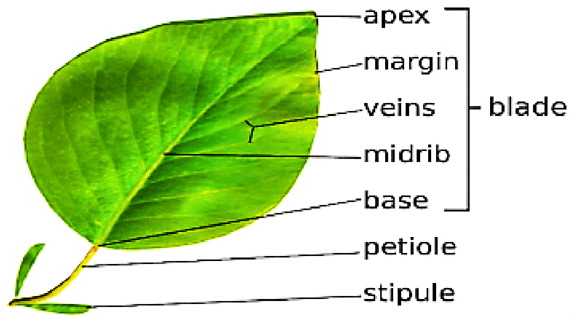

Fig 1.1 Exterior Leaf Parts

1.1.4 Plant Pathology and Pathogens

Plant pathology may be traced back to a concept called phytopathometry (from the Greek words "phyto-plant," and "pathos-disease," and "metron-measure"). Pathogens (infectious organisms) and local environmental conditions (physiological variables) lead to a wide variety of plant illnesses, and current agricultural science has developed a scientific strategy to combat these problems (Bock et al. 2021). It is also recognized in certain groups as a serious scientific endeavour whose goal is to safeguard the crops that feed people and animals. Numerous scientific disciplines, such as soil science, virology, genetics, plant breeding, weed science, biotechnology, meteorology, and mycology, are essential for the successful upkeep and prevention of plant crops and their associated diseases (Scholthof 2022).

The disease triangle is used to illustrate the central notion of plant pathology. The elements that contribute to illness development are symbolized by the points of the triangle. The pathogenic infection, the susceptible host and an ideal setting all make up this triad (Fischer and Ashnaei 2019). For a plant disease to occur, all three of these conditions must be met at the same time. Pathogens are unable to cause damage to plants unless both the correct host and the right environmental circumstances are present. Plant disease triangle are shown in Fig 1.2.

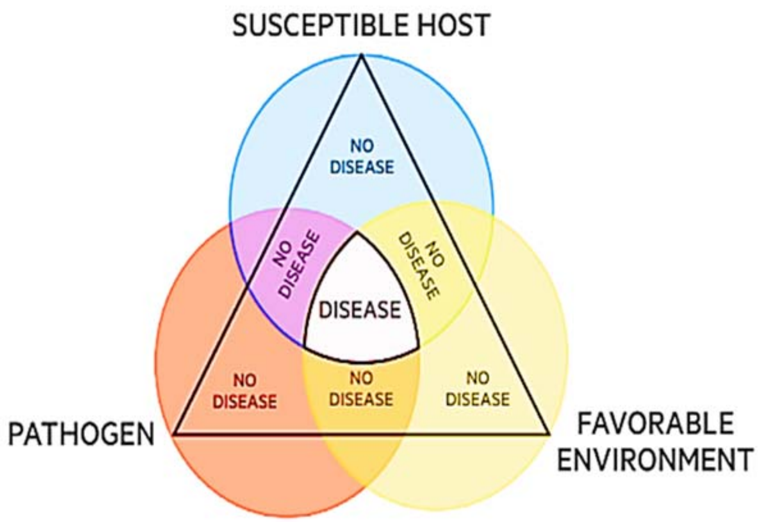

Fig. 1.2 Plant Disease Triangle

Pathogens cause suffering (pathos means "suffering" and genes means "creator of"). An infectious agent (bacteria, fungi, parasites, viruses, etc.) that causes disease in the host is called a pathogen. Humans, animals, plants, fungi and even microbes are all possible hosts (Timilsina et al. 2020). During the progression of illnesses, the impact of pathogens on the photosynthetic process is significant. Photosynthesis is a vital process for all plants to survive and thrive.

This photosynthesis may be used by plants to transform solar energy into chemical energy. By use of photosynthesis, chemical energy is transformed into forms that may be used by cells. In the presence of sunshine, the human hazard gas (carbon dioxide) in the atmosphere around a plant interacts with water molecules accessible in the vicinity of the roots to make glucose, releasing oxygen in the process. Given the vital role photosynthesis plays in plant life, it stands to reason that viruses that disrupt photosynthesis can cause plant disease. Diseases like leaf spots and blight, which attack the leaf tissue, limit photosynthesis by damaging the chloroplasts, which slows down the entire photosynthesis process (Singh et al. 2023).

A host is any organism (such as a plant) that provides shelter for and food to a parasite or pathogen. The host range refers to the various host plants that a parasite can live on. If a host can prevent, impede, or otherwise overcome the effects of a parasite or other detrimental forces, it is thought to be resistant to those factors. Depending on the specific pathogen or situation, a host plant may or may not be immune. Tolerance is the ability of a host to survive after being inoculated with a pathogen or exposed to a non-living element. When a host is susceptible to a parasite attack, the parasite can kill it. The plant (host) is what causes the illness to spread. If it is determined that host development is insufficient, the likelihood of disease is eliminated. This confirms that the progression of plant diseases corresponds to the developmental stage of the host plant. Also, the infection never happens at any time other than the developmental stage. In addition, the pathogen's development must be at a disease-causing stage before it may infect the host plant (Brooks et al. 2022).

1.1.5 Weather Conditions

The exact role that weather factors play in a disease’s onset varies greatly between pathogens. For fungi infections to develop, it needs to have both high humidity and specific temperature values. Plant development is affected by the primary weather factors of humidity, temperature, wind and light (Ahmed et al. 2020). A plant's susceptibility to disease increases dramatically if even one of the aforementioned weather factors is out of whack with the culture of that plant.

1.2 VARIOUS TYPES OF PLANT LEAF DISEASES

Leaves are the most commonly affected plant parts. Fungi and organisms similar to them are responsible for over 85% of all plant illnesses. Viral and bacterial organisms also cause other serious illnesses in agricultural crops.

1.2.1 Factors Influencing Leaf Diseases

Plant diseases are categorized depending on various aspects as shown in Fig 1.3. The primary taxonomy is divided into endemic, epidemic and sporadic, which is based on the duration it appears, called epidemiology (Riley 2019). The following describes in more detail:

- Endemic: When a disease is persistently widespread in a given location year after year, especially when it is of moderate to severe severity.
- Epidemic: A severe and widespread disease that occurs at regular intervals.
- Sporadic: A sporadic illness is one in which the pathogen affects a small number of plants but not others. It happens quite infrequently and only in small places.

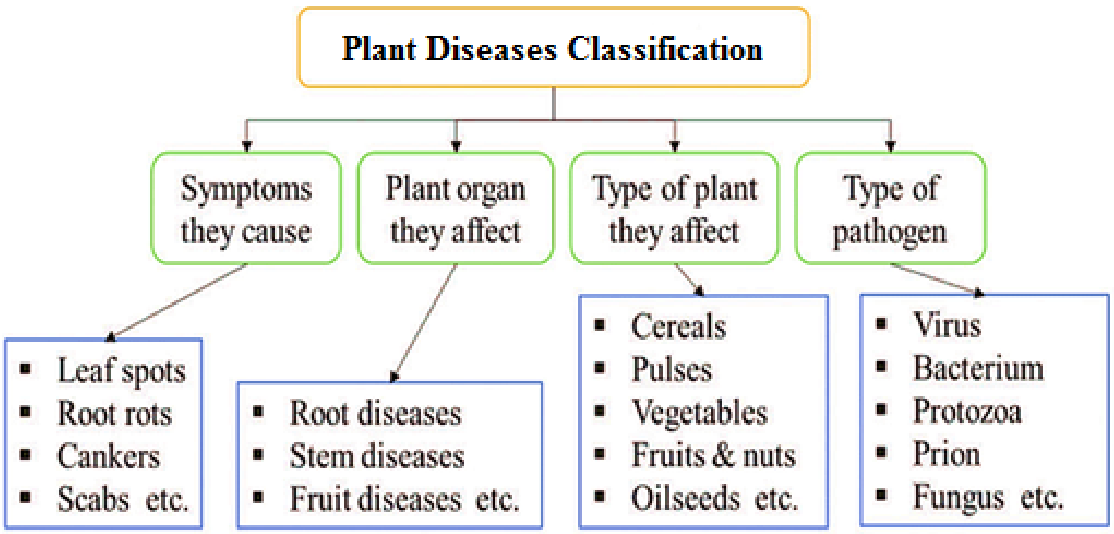

Fig. 1.3 Classifications of Plant Diseases

The secondary taxonomy classifies the disease according to the medium by which it spreads, such as soil, seeds, the wind, etc. According to the host plague, it is divided into crop illnesses, fruit illnesses, vegetable illnesses, etc. Plant diseases are categorized by the organs they attack: those affecting the roots, the stems, the fruits and the leaves (Lacaze and Joly 2020). Moreover, it is categorized into either biotic (infectious) or abiotic (non-infectious) depending on the cause of the illnesses (Nazarov et al. 2020).

Abiotic (Non-infectious) diseases: A disease that is disseminated because of an adverse atmosphere or lack of nutrients, is called non-infectious. A few adverse circumstances are given below.

- Unfair soil moisture
- Nutritional syndrome
- Unfair light intensity

- Optimal temperature imbalance
- Chemical pollutants
- Air pollutants

Bacterial, fungal, viral, nematode, and insect-borne illnesses are all examples of biotic (infectious) disorders. Parasitic organisms are abundant and can be found either within or attached to the host plant, where they cause disease and ultimately death. Depending on the host and parasite, the level of parasitism can range widely. Some kill their hosts quickly, while others can coexist with them for decades before finally killing them out. Some never kill the host plant, but they do impede its development, weaken it, or decrease its fruit yield. Some do not require a lot of food from the host plant, but their growth can hinder the plant's ability to carry out its normal processes. Different kinds of biotic plant diseases are presented in Fig 1.4.

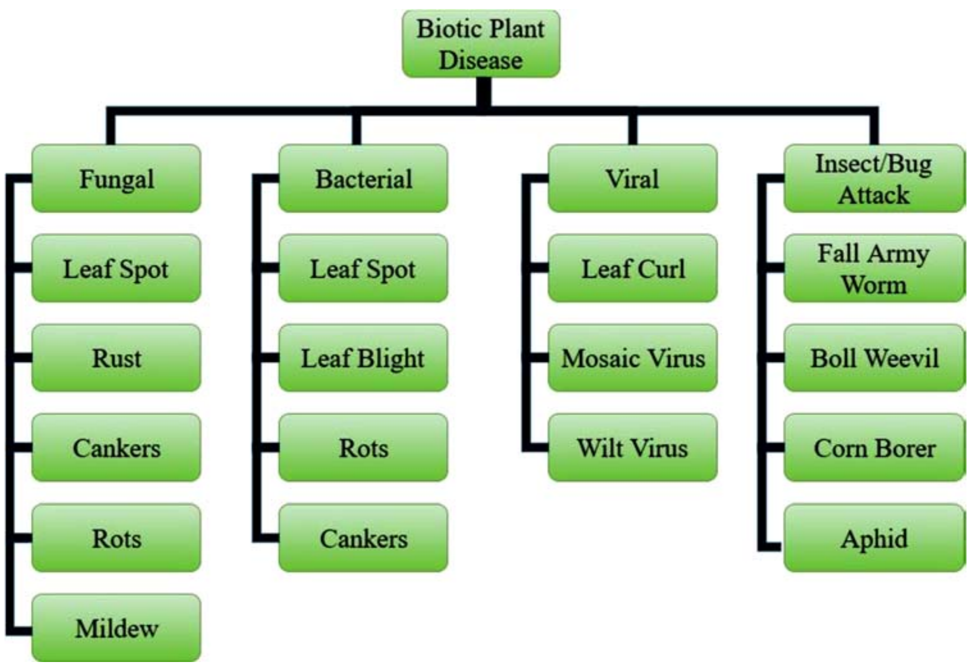

Fig. 1.4 Different Kinds of Biotic Plant Diseases

1.2.2 Fungal Diseases

Most plant parasites are fungi, which can lead to a wide variety of devastating diseases in plants. Fungi are responsible for the vast majority of plant illnesses. The majority of fungal diseases originate from contaminated seeds, soil, crop, or weed.

In its earliest stages, it manifests as grey-green spot patches, water-soaked at the base, or aged leaves. These spots get darker over time and a white fungal growth may appear on the bottom. Many sorts of vegetables may be harmed by fungus spores. These pathogens include Botrytis rots, anthracnose, downy mildew, powdery mildew and fusarium rots (Jain et al. 2019). Some main fungal plant pathogens are described below.

- Leaf spots: Spots on leaves, also known as anthracnose, scab, leaf blotch and shot hole, can be any size, shape, or colour. The fungi-caused spot has a yellow halo around it. After about a week, the spots on the leaves become noticeable. They have a reddish-brown, brownish, or yellowish border and are white to greyish-white in the center. The illness manifests itself first on the adaxial leaf surfaces and then spreads to the abaxial ones as shown in Fig 1.5.

Fig. 1.5 Leaf Spot Disease

- Leaf rust: Lesions that manifest as white, slightly elevated spots on the older, wrinklier epidermis of mature plants' leaves. Reddish-orange spore masses develop on the lesions over time. Pustules develop later, changing from yellow to green to black are presented in Fig 1.6.

Fig. 1.6 Leaf Rust Disease

- Late blight (Phytophthora infestans): It causes a systemic infection that kills plants. It usually occurs during vegetative growth and sometimes shows up after flowering. The first infected leaves appear as green and gray spots on the older leaves as shown in Fig 1.7. The spots become darker and white mycelial masses appear on the undersides of the leaves as the disease spreads in the plant.

Fig. 1.7 Leaf Late Blight Disease

- Early blight: The older the leaf, the lower on the epidermis the lesions will appear first. They look like tiny brown spots with concentric rings in a bullseye shape as shown in Fig 1.8. As the illness progresses, lesions grow throughout the leaves, turning them yellow and ultimately killing them. There is a widespread spread of the infection throughout the plant. Early blight can strike plants at any stage of development. It preys on plants that are weak or undernourished.

Fig. 1.8 Leaf Early Blight Disease

- Powdery mildew: Numerous narrow-host-range fungi are responsible for powdery mildew. It first shows up at the beginning of the plant's growth cycle. When leaves are infected with powdery mildew, they develop blisters that cause the leaves to curl upwards, revealing the lower epidermis. Mycelium, a fine powdery mass that can range in colour from white to grey, spreads across the infected leaves' upper surfaces as shown in Fig 1.9. Necrotic necrosis may cause leaf drop. Higher moisture levels in younger leaves make them more vulnerable to infection by the disease.

Fig. 1.9 Leaf Powdery Mildew Disease

- Downy mildew: Downy mildew (Plasmopara viticola) may affect a wide variety of plant species. Spots of yellow or white occur on the top surfaces of fully ripe leaves, as illustrated in Fig 1.10. Browning and possible abscission of infected leaves occur despite normal leaf moisture levels. Downy mildew is caused by a pathogen that is resistant to cold because it dwells in the plant and soil. The spores may be dispersed by everything from insects to wind to rain to even gardening implements.

Fig 1.10 Leaf Downy Mildew Disease

1.2.3 Bacterial Diseases

Agricultural wastes, splashes of water and rain spray, broken tools and contaminated workers' fingers are all potential factors for the spread of bacteria. Damage to stems, leaves, and roots, as well as central transport despite negative effects, can be caused by bacteria native to a plant's species. The symptoms of bacterial diseases include spots on the leaves, cankers, scabs, wilts, overgrowths, and a host of other abnormalities (Joshi et al. 2020). It would seem that the two most prevalent bacterial diseases affecting plants are citrus canker and potato scab.

The number of bacterial species that might cause sickness in plants is estimated to be about 200. They are at their most active when the environment is warm and humid. Several prominent bacterial diseases and their descriptions are provided below.

- Bacterial leaf spot: It manifests as water-soaked spots on older leaves, typically less than 0.25 inches in diameter as shown in Fig 1.11. These lesions tend to be triangular and bordered by leaf veins. A characteristic of this disease is a rapid darkening of lesions. The black colour of older lesions persists, but they dry out and take on a papery texture. New leaves are hardly ever affected by lesions.

Fig. 1.11 Bacterial Leaf Spot Disease

- Bacterial leaf blight: Water-soaked streaks varying in color from pale green to grey-green appear on the leaves of young plants infected with bacterial leaf blight, as seen in Fig 1.12. These streaks are especially evident around the leaf edges and tips. These sores join together, turning yellowish-white and becoming irregularly bordered. In time, the entire leaf turns white or gray and eventually wilts and dies.

Fig. 1.12 Bacterial Leaf Blight Disease

- Bacterial wilt: Clavibactermichiganense subsp. michiganense causes bacterial canker and wilt of tomato. Leaves, stems and fruits develop spots, and the plant itself wilts and dies. White, blister-like spots in the margin of the leaves on the lower part of the plant often turn brown and may coalesce with age. Eventually, the leaves will turn brown and wither after wilting and curling upward and inward as shown in Fig 1.13. The wilt may spread slowly from one leaflet to the next, eventually wiping out the entire plant.

Fig. 1.13 Bacterial Wilt Disease

1.2.4 Viral Diseases

There are many possibilities for virus transmission from plant to plant. All the plantations' genomic configurations allow for the transmission of genetic information from parent to offspring. Although other viruses may also affect the buds, seeds and roots, those that affect the leaf are the most obvious to the naked eye. Virus infection detection is notoriously difficult. Inflammation causes the leaves to become rumpled and twisted, which can slow growth. Viruses are not airborne or waterborne like bacteria and fungi (Wang et al. 2022). They need to physically enter the facility instead. Insects are a major source of virus transmission. Insects spread plant viruses from infected plants to uninfected ones when they feed on them. The foremost viral diseases affecting plant leaves are explained below.

- Mosaic virus: One of the most prevalent mosaic symptoms is mottling, which appears as alternating light and dark green or yellow spots or streaks on the leaves (see Fig 1.14). The leaves may be stunted, twisted, or puckered, and the veins may be narrower than normal or banded with dark green or yellow.

Fig. 1.14 Leaf Mosaic Virus Disease

- Yellow dwarf: The yellow dwarf virus causes discolouration of the leaves and the tips of the plants, which in turn slows photosynthesis, stunts growth and reduces seed grain production as shown in Fig 1.15.

Fig. 1.15 Leaf Yellow Dwarf Disease

- Leaf curl virus: Its signs are thickened leaves, as well as upward and downward curling as shown in Fig 1.16. Young leaves and shoots on the infected plant are small and stunted. It develops a bushy, short stature and grows at a snail's pace. The leaf's edge can curl inward or up and has a yellowish, stiff margin. The leaves develop a leathery thickening and become abnormally large. The new leaves are a yellowish green and have a cupped, thick, rubbery appearance.

Fig. 1.16 Leaf Curl Virus Disease

1.3 VARIOUS THREADS IN AGRICULTURE

This research focuses on finding a more efficient strategy to deal with weeds, agricultural diseases and pests. The presence of weeds in a crop field impairs the yield, quantity and quality.Agricultural productivity is also heavy impacted by crop diseases, which can damage an entire field of crops resulting in a significant harvest loss. Pests are another major threats to agriculture productivity.

1.3.1 Overview of Pests and Types of Pests

The words pest and pestis, both meaning plague in French and pest in Latin, are the etymological ancestors of the English word pest (Ferreira et al. 2021).

- An animal is considered a pest if it is harmful to people or their property in some way
- Large populations of organisms that pose a threat to human health, safety, or economic interests are considered pests
- A pest is any organism that causes or is likely to cause significant harm to man or his property
- Insects are considered pests when their population levels are high enough to have a negative financial impact
- Pests are organisms that cause problems for humans by, among other things: (i) damaging crops, forests, and ornamentals; (ii) annoying people and killing livestock, and (iii) destroying or devaluing stored goods
- Pests include not just insects, nematodes, mites, snails, slugs, and the like, but also rats, birds, and other vertebrates.

The pests are categorized into the following types depending on their occurrences:

- Regular pests: These are closely related and often appear on crop. The Rice Stem Borer and the Brinjal Fruit Borer are two prevalent examples.
- Occasional pests: This is very uncommon and unrelated to anything else. The rice caseworm and the mango stem borer are two such instances.
- Seasonal pests: These tend to take place once a year, at a certain time of year. Mango hoppers and the red hairy caterpillar that feeds on groundnuts are two such examples.
- Persistent pests: Chilli thrips and mealy bugs on guava are two examples of pests that plague the crop all year and are notoriously difficult to eradicate.
- Sporadic pests: Such occurrences are often alone and last for a while. The coconut slug caterpillar is one such instance.

The pest categories depending on the plague level are the following:

- Pest epidemic: An unexpectedly severe pest infestation in a certain area at a certain time. Tanjore's Rice Brown Plant Hopper (BPH) and Madurai and Pollachi's Rice Husk bio-Charcoal (RHC) are only two examples.
- Endemic pest: The pest is just barely noticeable in certain places, usually confined to one geographical area, as the Rice gall midge in Madurai or the Mango hoppers in Periyakulam.

1.3.2 Causes of Pest Outbreak

The human activity that disrupts the natural equilibrium of an ecosystem is a major contributor to pest problems (Thiri and Yang 2022). Some examples of human interference are,

Forest destruction and conversion to agriculture

- Insects and other pests that traditionally feed on trees in the forest are now eating farm produce.
- Biomass per unit space is higher in forests than in farmland.
- Changes in climate have an effect on insect growth and development.

  Elimination of Predators

- Natural predators are killed as a result of excessive insecticide usage.
- This impacts the biological control system and causes pest outbreaks, for example, synthetic pyrethroid insecticides kill natural predators.

  Intensive and extensive agriculture

- Pest populations increase as a result of intensive monoculture.
- Farming of prone varieties on a large scale in a region with no food conflict leads to increased multiplication. Some examples are sugarcane and rice stem borers.

Emergence of novel species and plants

- Pests extend in species with positive physiological and morphological characteristics.
- Succulent, dwarf rice varieties, Cambodia cotton, spotted bollworm hybrid sorghum, cumbu shoot flies, and gall midges are all examples of plants that need help from pests in order to thrive.

Raised agronomic activities

- Raised N fertilizer: a lot of rice plants have leaf folders.
- Earlier planting: Boosts BPH and leaf folder health.
- Granular insecticides: Effect on rice phytotonics.

Emergence of novel pest in novel atmosphere

- Lack of indigenous predators in a new area contributes to pest expansion.
- Apple wooly aphid grew quickly because of lack of parasite (Aphelinus mali).

Chance of pest's emergence from foreign republics (via air/sea ports).

Some examples are

- Plutella xylostella, the diamondback moth, on a cauliflower.
- Phthorimaea operculella, the potato tuber moth
- The Scale of Cottony Puffiness Wattle tree covered with icerya purchase
- The woolly aphid, Eriosoma lanigerum, on an apple
- Heteropsylla cubana (the psyllid) on subabul
- Nursery plants are susceptible to the spiral whitefly, or Adeyrodichus dispersus.

  Resurgence: The use of pesticides resulted in a dramatic rise in pest numbers, despite the fact that they had initially caused a significant drop in those numbers.

- Deltamethrin, Quinalphos, Phorate - Increased prevalence of BPH in rice
- Synthetic pyrethroids - Cotton whiteflies
- Carbofuran - a leaf-folding agent used in rice

1.3.3 Different Pest Management Strategies

Pest control solves agricultural, urban, and wildland-insect pest problems with minimal environmental impact (Tay et al. 2020). It uses biological and structural methods to deter or reduce pests, as shown in Fig 1.17, to control a variety of pests.

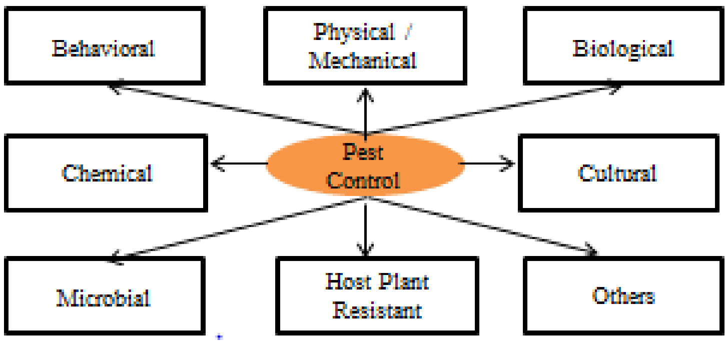

Fig. 1.17 Pest Control Strategies

Host plant resistance: Tolerating, avoiding, or recovering from pest attacks are all goals of host plant resistance strategies. Insect-resistant varieties of crops can be developed through conventional breeding or genetic engineering. Such plants have biochemical, morphological, or physical characteristics that make them less desirable to a pest, thereby reducing the pest's ability to feed and reproduce effectively on the plant in the wild (Egan and Stiller 2022).

Cultural control: Altering planting dates, using high-yield pest-tolerant varieties, proper plant spacing, using bio-fertilizers, intercropping trap crops, and destroying crop residues are all examples of cultural control strategies that work to reduce pest infestation (Bakshi et al. 2022). Cultural methods of pest management reduce pest populations and break the cycles that perpetuate them.

Biological control: This method employs predators, parasites, and pathogens to reduce pest populations, among other natural enemies (living organisms). Some of the ways that natural enemies of agricultural pests are cultivated include creating an environment conducive to natural enemy population development and introducing commercially available natural enemies of pests into the crop (Poveda 2021).

Behavioural control: The goal of the behavioural control strategy is to reduce the population of a pest by preventing males from mating with females through the use of chemicals (pheromones) (Bakthatvatsalam et al. 2022). Pests can be lured into a trap (called a "pheromone trap") with the help of these pheromones.

Physical and mechanical control: By adjusting various environmental and physical factors, the physical control strategy makes the surrounding area uninhabitable for pests (Lee et al. 2023). Many techniques are used to make the crop environment unfavourable for the growth and survival of the pests, including the manipulation of temperature, flaming, moisture and light. In the field, instruments using acoustics, ultraviolet radiation, infrared radiation and radio frequency are used to exterminate pests. Pests are killed instantly with the use of light traps in this technique. The number of insect pests in the crop can be reduced through the utilization of mechanical control strategies, such as shaking plants, combing, hand nets and handpicking the plant leaves with the pest's eggs and larvae.

Microbial control: In a microbial control Integrated Pest Management (IPM) strategy, microorganisms like fungi, viruses, and bacteria are deployed as biological control agents. The pest population can be drastically reduced by using these biological control agents to introduce disease to the insects (Wagemans et al. 2022). Potentially less harmful to the environment than traditional chemical pesticides would be those based on microorganisms.

Chemical control: Synthetic chemical pesticide-based chemical regulation is the least preferred IPM strategy due to environmental contamination and numerous human safety threats. Chemical pesticides are divided into several categories based on their mechanism of action (Stejskal et al. 2021). The insect pest will develop resistance to the chemical pesticide if it is used repeatedly on the crop. That's why it's smart to switch up chemical makeup every so often. To lessen their impact on the environment, the government has imposed time and quantity restrictions on the use of certain chemical pesticides. They are one of the most efficient ways to prevent pest infestation, but they have their drawbacks.

1.3.4 Leaf Disease and Pest Detection in Agriculture

Experts need to keep a sharp watch out for plant leaf illnesses in order to diagnose them. Smaller farmers can't afford to hire the pricey team of professionals that would need to monitor the plant around the clock. Farmers in other nations also lack access to modern information technologies and professional advice in real time.

Automatic disease detection is an easy and low-cost method based on the observation of symptoms on plant leaves. Computer vision techniques can be used to guide, inspect and manage robotic processes automatically (McDonald et al. 2022). In addition to being a time-consuming and error-prone process, identifying plant leaf diseases visually has a very limited scope. However, the time and energy needed are reduced and the detection accuracy is increased when using an automated detection strategy. Brown spots, yellow spots, early scorch, late scorch, and infections from fungus, viruses, and bacteria are all quite common plant diseases.

Improper plant maintenance may have far-reaching effects on output quality, yield, and efficiency. A few automated methods for identifying plant diseases are helpful because they simplify crop monitoring on big farms (Domingues et al. 2022). Moreover, the presence of disease symptoms on plant leaves allows for early detection and treatment.

Symptoms often include stunted development, irregular leaf colour and growth, and pods that dry up and split apart. It's very uncommon for common insect pests and plant diseases to cause substantial losses in crop yields or even death of plants. Now is the time for rapid diagnosis and management actions to avert serious crop damage. Fruit, stem, and leaf are only some of the plant parts that might get infected (Khakimov et al. 2022). If a leaf is of high quality, it will not have any noticeable flaws or be in short supply. Crucial factors include seeding, temperature, transplanting, and harvesting.

The main linked catalyst of leaf-related illnesses can be categorized as either infectious or non-infectious. Diseases in leaves may be caused by a wide variety of pathogens, including bacteria, mycoplasma, fungus, viruses, nematodes, and viroids (Nazarov et al., 2020). Within or upon a host, an infectious agent may proliferate and spread to additional vulnerable organisms. Non-infectious plant diseases, on the other hand, can be traced back to factors outside of the plant itself, such as a lack of a necessary mineral or an inadequate supply of water or air.

It is essential to immediately identify plant diseases and adopt suitable management measures in order to guarantee a high-quality crop. Using image analysis and machine vision technologies, plant leaf diseases may be swiftly and correctly identified (Tian et al. 2020). In recent years, there has been substantial advancement in the capacity to isolate plant illnesses, extract key traits, and diagnose those diseases. However, because of noisy samples, low rate recognition of disease regions, and a bigger feature dimensionality, accurately and efficiently identifying illnesses in a shorter amount of time is a major challenge (Ali et al., 2019).

1.3.5 Effects of Environmental Factors on Leaf Disease

Crops are vulnerable to disease infections, mainly caused by aggressive environmental conditions such as soil and weather factors. The likelihood that a leaf disease may become epiphytic depends on a number of environmental parameters, variables such as temperature, humidity, soil moisture, pH, soil type, and fertility.

1.4 INTRODUCTION TO DIGITAL IMAGE PROCESSING

Image processing is a method that analyses and modifies an image to either enhance its quality or learn something new about it. It's a form of signal processing wherein a still image, video frame, or set of attributes associated with an image serve as input. These days, multimedia information is increasingly used. As a result, image processing remains a dynamic field of study in the sciences of both engineering and computer science (Ngugi et al. 2021). Below are the three primary phases of image processing.

- Image collection
- Image analysis and manipulation
- Obtain the modified image or produce the analysis report

Image processing is divided into analog and digital. Analog image processing makes use of physical copies of images, such as printouts and photographs, and employs a variety of visual analysis approaches. Machines are utilized for the evaluation and manipulation of digital images in digital image processing.

The five most common applications of image processing are:

- Visualization
- Image sharpening and restoration
- Image retrieval
- Pattern or object recognition
- Image classification

Digital images specifically plant leaf images are the focus of the proposed research. Digital image processing yields a picture in the form of a two-dimensional array, where each cell's value is the intensity of an area of the picture located at a certain location in space. For a computer to process an image digitally, the image must be converted into a numerical representation. A picture element, or pixel, is a number that represents the brightness value at a specific location in an image and is represented by two coordinates. The values of the pixels in a digital image are discrete. Despite much larger images becoming the norm with digitization, the typical resolution of a digitized image is still 512 pixels on a side or about 250,000 pixels in total.

There are three primary kinds of operations that a machine can carry out: point operations, local operations, and global operations. Any given pixel in the "destination" image is "operated on" depending on the value of a single pixel in the "source" image. In local operations, the pixel value of the output image is determined by a large number of neighbouring pixels in the input image. Only one output image pixel's value is determined by the values of all input image pixels in a global operation. Also, digital images come in three varieties: grayscale, binary and colour. The intensity in grayscale pictures can be anywhere from 0 to 255. There are no gray areas between 0 and 255 in a binary intensity scale. Each pixel's value in a coloured image represents one of the three basic colours (RGB): red, green, and blue. Some image-processing applications in agriculture are the following:

India's economy relies heavily on its agricultural sector. Agri-based image recognition is becoming an increasingly important and active area of study. Image processing has emerged as a valuable tool for investigators across many disciplines, especially in agriculture. Images captured by sensors, aircraft, or satellites are analyzed to guide farming practices. After that, the photos will be manipulated and interpreted by computers using image manipulation tools. New tools for collecting and analyzing data have made strides toward solving a variety of agricultural problems. For instance, image analysis could be used in smart agriculture to sort infected leaves, roots and seeds, measure the infected region by infection and evaluate the pathogen by identifying the colour scheme, form and scale of the infected region (Shafi et al. 2019; Sishodia et al. 2020).

- Pest management and crop preservation are examples of crop management (Tewari et al. 2020)
- Nutritional constraints yet also organic matter, including malnutrition and crop quality are recognized (Kashyap and Kumar 2021)
- Vegetables and fruit classification experience common testing, filtering and ranking schemes (Tripathi and Maktedar 2020)
- Land and crop measurement, as well as entity recognition, are examples of Geographic-Information-System (GIS) applications (Hassan et al. 2021)
- Recognizing plant infections, including identifying plant leaf infections based on colour, texture, smoothness and so on (Vishnoi et al. 2021)
- Weed identification (Wang et al. 2019) and fruit grading (Behera et al. 2020)

Most plant life relies on the power of its leaves to thrive. Pesticides used to prevent diseases on plant leaves will have devastating effects on all forms of life. Early detection of plant diseases is essential to bolstering the agriculture sector and the economy as a whole. Due to the impossibility of manually inspecting plant leaves for illnesses, rapid and automated methods for disease detection in leaves are urgently needed (Ngugi et al. 2021).

The first step in leaf disease detection is to acquire a digital image from any setting using an acquisition mechanism. Many challenges make it difficult to detect diseases in plant leaves, including (i) poor image quality, (ii) noise and background in the acquired image, (iii) difficulty in identifying the precise leaf region where the disease is located, and (iv) climate-related changes in leaf characteristics like colour, size and texture. Image processing and AI techniques can solve these problems and more, allowing for the efficient and automatic detection of leaf diseases with minimal computational effort (Yağ and Altan 2022). The primary image processing methods needed for plant leaf detection are shown in Fig 1.18.

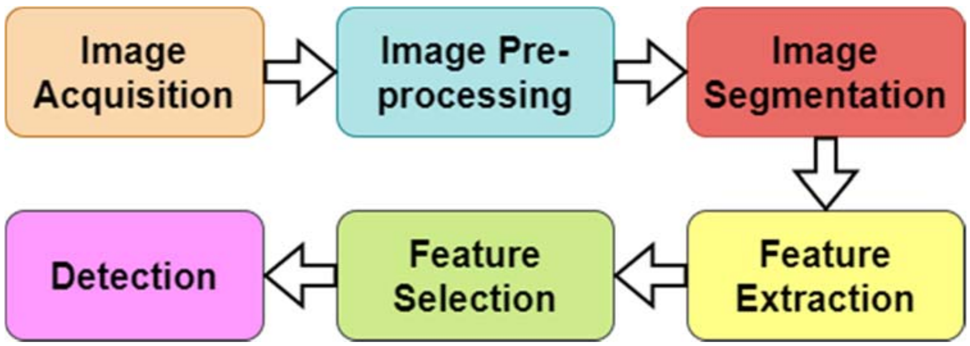

Fig. 1.18 Fundamental Steps in Leaf Disease Detection

1.4.1 Different Steps in Digital Image Processing in Agriculture

Low-level processes, intermediate-level processes, and high-level processes are all part of the digital image processing toolkit. Noise reduction and image sharpening are examples of low-level process operations. An image is both the input and the output of a computer processing system in the case of a low-level procedure. However, an enhanced image is produced.

In intermediate processing, an improved image serves as the input and the results are similar to features or attributes. Segmenting an input image into distinct regions, like a healthy region and an infected region, is an example of a mid-level process. A higher-level process takes feature-like input into a processing system and produces similarly high-level results. For instance, in disease recognition, the images are analyzed using the extracted features to classify healthy and infected leaf images. Capturing the images, preprocessing them, segmenting them, extracting features from them, and detecting them are all crucial steps in image-based leaf disease identification.

1.4.1.1 Image Acquisition

It is possible to obtain a digital image by either directly capturing it with a digital camera or by transforming an analog image. The goal of a digital image capture system is to provide a numeric representation of an optical image.

Quality of the captured images is crucial to the reliability of the training images utilized. Integrated Pest Management (IPM) Images, PlantVillage Images, and the APS Image database are some of the well-used datasets in this field (Sanju and Velammal 2021). The University of Minnesota Extension website also features visuals that elaborate on the underlying theory. Data from the International Rice Research Institute (IRRI) and the International Network for the Improvement of Banana and Plantain (INIBAP) have been used in some of these studies with the authors' express consent. Very few people have observed more than one culture over time. Some have resorted to using scanned photos. Self-collected image datasets have been used in a variety of studies, both in lab settings with consistent lighting and in the field with variable lighting and complex backgrounds. Images of the inside of a lab or sampling box are taken for the same purpose of regulating the lighting. A few studies have collected images with intricate field settings.

Sample image quality is quite sensitive to camera model and shooting perspective. While some of these investigations have utilized more specialized techniques, the great majority have relied on digital cameras with an optical axis perpendicular to the leaf plane.

Capturing images requires the use of specialized hardware and software, including various types of Charge-Coupled Device (CCD) colour cameras. An Android phone can also be employed to take a picture of a leaf from a predetermined distance. A multispectral camera with a portable spectroradiometer is also equipped to capture leaf images (Rosas et al. 2022). Currently, a hyperspectral imaging system is utilized to obtain the leaf images (Mishra et al. 2020). Images captured in a lab setting would be simpler to process. The level of image detail is affected by the equipment and methods used. So, the background of the acquired image and the conditions under which it was captured affect the effectiveness of a plant disease detection system.

1.4.1.2 Pre-Processing

When referring to actions on pictures, the phrase "image pre-processing" means "the simplest possible level of abstraction". The goal is to enhance image data by getting rid of background noise or boosting a few key elements that will be utilized in further analysis and processing. In this case, a distorted pixel is corrected, its value is brought up to the mean of its surrounding pixels.. Based on the size of the pixel neighbourhood, a new pixel's illumination is calculated and this is how image pre-processing techniques are divided up.

Several different approaches to pre-processing are taken into account. One of them is picture clipping, which involves cropping the image to get the desired area. The retrieved picture is also improved with the help of a smoothing filter. Captured photographs may have their contrast improved via the application of image processing methods. There are three phases involved in the pre-processing phase: clipping, smoothing, and enhancement. There are a variety of reduction methods that may be used to achieve denoising. When salt and pepper noise is present, choosing the right threshold may improve a medium filter's performance. The image will have a salt and pepper effect, featuring brighter pixels in the dark region and darker ones in the light region. Because the pictures were shot in the actual world, imperfections like dust, spores, and water stains are possible. Eliminating picture noise by alterations to pixel values is a primary goal of data pre-processing (Zamani et al. 2022). Thereby, the overall picture quality improves.

Pre-processing techniques are considered for reducing image noise or eliminating unwanted elements. It is important to "clip" or "crop" the image of the leaf to get the desired result. It is possible to create this smoothing of the picture by using the smoothing filter. Enhancing contrast in a picture. Once the picture of the plant disease has been captured, histogram equalization is used to spread the image's intensities out throughout the histogram. The cumulative distribution function is helpful for assigning intensity levels. There are several pre-processing methods available for eliminating noise in a picture or on any other object.

Image Cropping and Filtering

Image pre-processing starts with cropping. The Region-Of-Interest (ROI) is determined and a few redundant areas are removed. Image filtering techniques change the brightness of an output image by using a small neighbourhood of a pixel from an input image (Ngugi et al. 2021). Smoothing reduces image noise and irregularities.

Noise Removal

Noise removal methods are Kalman filter, band-pass filter, linear smoothing and sharpening filter, median filter and wiener filter. Median and rank filters are popular because noise is common. Sharpening is done with a Laplacian filter. Histogram equalization and Gabor wavelets also filter and control lighting conditions (Vishnoi et al. 2021). Recent enhancements include anisotropic diffusion. Neighbourhood mean, frequency low-pass and spatial low-pass filters are also used.

1.4.1.3 Segmentation

Image segmentation distinguishes the image's most important regions that are distinct and must meet consistency criteria in specific areas. It divides an image into several discrete regions with pixels that are highly similar and contrasted. Image segmentation methods include threshold, edge, cluster and neural network. A classical clustering method for image segmentation is the k-means method. It is simpler and faster than hierarchical clustering. When processed, leaf image segmentation partitions the image into similar parts (Iqbal et al. 2018). Mostly, the segmentation is done by Otsu's method and K-means clustering.

Threshold Segmentation Techniques

Thresholding makes it easier to divide up a dataset. By deciding on a threshold T, which divides picture pixels into regions and distinguishes objects from the background based on their level distribution, thresholding transforms a multilevel image into a binary image. Grayscale images may be transformed into binary with the help of a process called thresholding, which gives a value of zero to pixels below a certain threshold and a value of one to pixels above it. (Sun et al., 2018) Two well-liked approaches to segmentation are the iterative technique and the Otsu threshold.

Clustering Segmentation Techniques

Data is organised into coherent groups for easier review. When it comes to grouping and dividing up data, K-means and Fuzzy C-means algorithms are utilised (Tian et al., 2019).

1.4.1.4 Feature Extraction

To facilitate learning and generalization, feature extraction begins with measurable data and generates meaningful, non-repetitive values. If an algorithm's input data is too large to process and repetitive (Some examples are the redundancy of images introduced as pixels), it can be transformed into a feature vector (Vishnoi et al. 2022). It can wisely predict affected areas by extracting shape and texture features. Area, color axis length, eccentricity, solidity, and perimeter are the characteristics of shapes. In terms of texture, it may look at contrast, correlation, energy, and mean. Leaf disease detection can use colour, texture, morphology, edges, etc. Texture defines image roughness, colour sharing and rigidity. Three feature extraction methods are used (Archana et al. 2022). These include,

- Texture-based feature extraction: Image processing computes image textures using matrices. The texture shows an image's colour or intensity distribution or selected area. Since it only defines format of colour or intensity, it cannot define image features like colour. It also can't find colour similarities from the feature set
- Shape-based feature extraction: It measures feature similarity between shapes. The shape is a key visual feature to describe image content. Shape content is difficult to describe because measuring shape similarity is hard. Therefore, colour-based feature extraction is typically used
- Colour-based feature extraction: Color-based feature extraction is employed because of its accuracy, efficiency, and small memory footprint. The color spectrum is represented by the R, G, B and H, S, V (hue, saturation, value) models. Humans recognize colour as a mix of primary colours: Red, Green, and Blue. Adjusting such primary colours produces other colour models

1.4.1.5 Feature Selection

Feature selection removes irrelevant, repetitive and noisy features to improve detection accuracy. It selects a subset that represents the entire feature set based on relevance and redundancy. Relevant features visualize system response as desired. Conversely, repetitive features are more correlated. Features with high correlation do not provide more information. Robust features provide a higher correlation relevant to decision-making and unrelated to other features (Bhagat and Kumar 2023). It uses wrappers, filters and embedded techniques.

- Wrapper technique: Predictive models rank feature subsets in wrapper methods. The model is trained with each new subset and then validated using the hold-out data. These strategies are computationally costly due to the need of training a new model for each subset, but they provide a feature set with improved accuracy for the target model or for recurrent problems.
- Filter technique: Filter methods use proxies instead of error rates to rank feature subsets. Though computationally easier than wrappers, filters provide a feature set that is not optimized for a predictive model.
- Embedded technique: These are a catch-all category of model creation that select features

1.4.1.6 Detection

Since plants are susceptible to many diseases, leaf disease detection is crucial to crop yield and production. Without proper care, it damages plants, affecting product quality and productivity. The economy relies on agricultural productivity. Since plant diseases are natural, disease detection is important in agriculture. An automated plant disease detection reduces monitoring in large crop farms. It detects diseases early on plant leaves (Kale and Shitole 2021). Various traditional classification approaches like decision trees, K-Nearest Neighbor (KNN), Support Vector Machine (SVM) and Artificial Neural Network (ANN) are used for leaf disease detection.

1.4.1.7 Ensemble Classifiers

Multiple learning algorithms are used in ensemble classifier approaches to boost detection performance above that of a single algorithm. In contrast to a statistical ensemble in statistical mechanics, a ML ensemble is a trustworthy limited collection of alternative models. It usually allows an extremely scalable form among those alternates (Yousuf and Khan 2021).

1.4.1.8 Performance Validation

After training, the classifier tests images from the database and determines model performance. The model or classifier is validated if it executes well. The model performance is determined based on various evaluation metrics like accuracy, specificity and sensitivity.

1.5 LEAF DISEASE IMAGE DATASET

Table 1.1 shows the most often used benchmark datasets for leaf disease and pest identification. The table lists the dataset's name, brief explanation, data category, as well as the diseases and pests that are included in the dataset. Researchers and programmers may utilize this data to evaluate and contrast the efficacy of their algorithms and models with those of the community's best efforts.

Table 1.1 Standard Leaf Disease Image Datasets for Leaf Disease Classification

Dataset Name	Description	Data Category	Disease/Pest Classes Included
PlantVillage	An open dataset including over 54,000 images of both unhealthy and healthy leaves has been compiled by experts and curious onlookers alike.	RGB images	There are 38 plant species, and 38 groups of diseases.
PlantClef	A collection of more than 9000 leaf images used in the yearly Plant CLEF benchmarking competition.	RGB images	Multiple plant species and disease classes
Open Plant Disease Dataset	Eight thousand images of leaves, culled from academic studies and citizen scientists.	RGB and infrared images	Multiple plant species and disease classes

Dataset Name	Description	Data Category	Disease/Pest Classes Included
Plant Disease Detection in Cotton Images	The National Cotton Council of America's collection of over 5,000 leaf photos used in disease detection studies.	RGB images	Cotton leaf diseases
AGRONOMI-Net	The AGRONOMINet project has amassed over 3,000 crop photos for disease detection studies.	RGB azznd thermal images	Multiple plant species and disease classes
Northern Leaf Blight (NLB) lesions	Collection of field-captured pictures of maize plants with NLB symptoms.	RGB	NLB diseases
Insects from rice, maize and soybean	Insect data collected from field studies of rice, maize, and soybean plants.	RGB	Rice plant hoppers, Brown plant hoppers and Whiteflies
Pest and Disease Image Database (PDID)	Seven thousand and more images of healthy and ill plants, taken in the field.	RGB	Multiple plant species and diseases
Plant Disease and Pest Recognition (PDPR)	Over 30,000 field-collected plant photos, including both diseased and healthy specimens.	RGB	Multiple plant species and diseases
Robusta Coffee Leaf (RoCoLe) dataset	Over 1560 photos of normal and diseased coffee leaves collected from an unconstrained outdoor environment.	RGB	Red spider mite and rust diseases
Brazilian Arabica Coffee Leaf (BRACOL) dataset	Collection of over 1 747 images of Arabica coffee leaves from Santa Maria de Marechal Floreano in Brazil's Espirito Santo National Park's highland regions.	RGB	Leaf miner, leaf rust, brown leaf spot and Cercospora leaf spot
Rice leaf disease dataset	More than 120 white-background images of rice leaves were taken at Shertha, Gujarat, India, close to the city of Gandhinagar.	RGB	Bacterial leaf blight, brown spot and leaf smut

Dataset Name	Description	Data Category	Disease/Pest Classes Included
Plant pathology dataset	Collecting apple leaf images from Cornell AgriTech's Geneva, New York, USA, orchard resulted in a collection of more than 3,651 images.	RGB	Multiple apple foliar diseases
Citrus dataset	More than 759 images of citrus leaves, both healthy and afflicted, make up this collection.	RGB	Black spot, canker, greening and melanose
Database for Diagnosis and Monitoring Plant Diseases (DiaMOS Plant)	More than 3006 images of pear fruit leaves, both healthy and unhealthy	RGB	Spot, curl and slug diseases
PlantDoc dataset	More than 2,598 images of healthy and sick leaves, gathered from specialists throughout the world, make up the collection.	RGB	13 plant species and 17 disease classes

1.6 ROLE OF ARTIFICIAL INTELLIGENCE IN AGRICULTURE

Globally, the quality of seeds, soil monitoring, weather forecasts, agricultural analysis, markets, and distribution networks are all being enhanced by technological advancements. With the use of cloud computing, data ecosystems, the Internet of Things (IoT), and artificial intelligence (AI), agricultural productivity may be boosted. The process includes insect control, harvesting, irrigation, chemical spraying, and smart farming. Automation of irrigation systems with AI improves productivity in the agricultural supply chain (Javaid et al., 2023).

The need for high-quality water has expanded in response to the rising demand for food. Thus, AI helps with efficient irrigation, water level, soil temperature, nutrient content, disease detection, and weather forecasts. A few major applications of AI models in agriculture are listed in Fig 1.19. The design of models can use ML and soft computing techniques from AI. Using plant growth images, AI models can be developed.

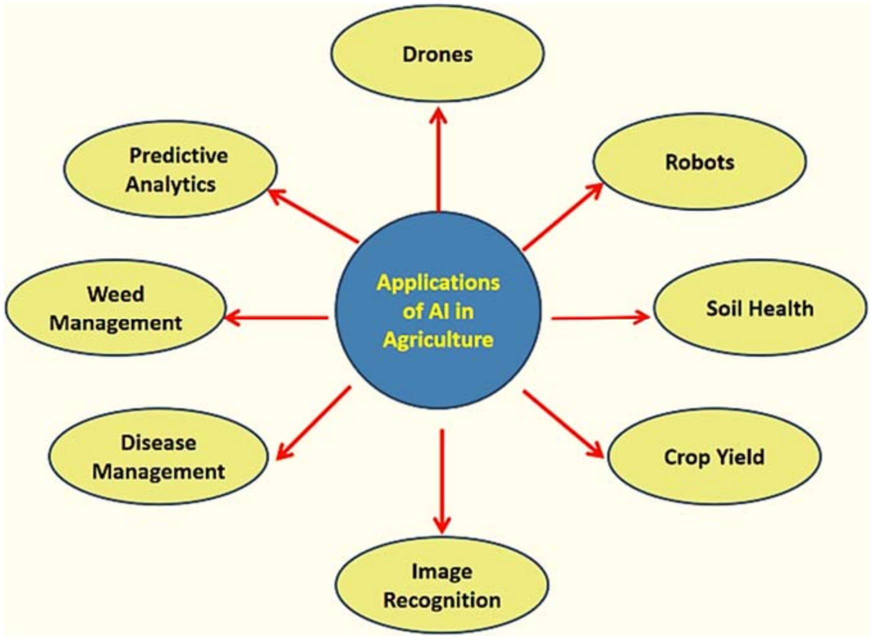

Fig. 1.19 Types of AI Applications in Agriculture

Drone and satellite imagery, data processing, agricultural monitoring and management systems, disease and pest diagnosis, and fertiliser scheduling are just some of the many applications of artificial intelligence in the agricultural sector. Chemical spraying, harvest timing, and shelf life are just some of the things that ML can foresee.

There is no uniformity in the timing or size of the harvest for bananas cultivated under the same conditions. The fertilizer might be spread out evenly, yet this still happens. Built-in intelligence models with the appropriate expertise do the necessary analysis and provide the necessary solutions to these problems.

Farmers now get AI-based loans from banks. AI data analytics can determine payback capacity before dividing the amount. Insurance companies are using AI frameworks to improve crop insurance processes, preventing delays and speeding up claim settlements. Farming and harvesting with robots and intelligent machines saves a lot of labour (Wang et al. 2021). The next generation of agricultural AI should be able to tell farmers which seeds are readily available for germination and blooming. For framer distribution, many Indian seed banks must coordinate with the AI models. The soil, market, weather and availability determine the seed recommendations. AI models may also be used to identify plant diseases that manifest in the leaves, stems, and other sections of the plant (Singh et al. 2022).

1.6.1 Machine Learning Techniques

Many ML techniques are used for leaf disease and pest identification in plants. KNN, SVM, logistic regression and decision trees are the most popular methods (Jackulin and Murugavalli 2022). These methods improve classification model feature extraction when used with various image pre-processing methods.The following ML algorithm such as

- KNN: The memory-based, supervised KNN classifies input based on similarity. It calculates neighbour distances, finds closest neighbours and votes for labels. Distance functions calculate data similarity. Most common distance functions are Euclidean, cosine, correlation, Manhattan and Murkowski. Its main benefit is no model or parameter tuning. It classifies unlabelled objects using nearby labels. The algorithm slows down with more data and features and performs better with fewer features. The binary KNN classifier classifies new examples using different K values. If the K value changes for a problem, the classifier's performance may change. The K value identifies neighbour data, and the distance between neighbour data and new data is the most important labelling parameter
- Decision trees: Another simple and widely used supervised ML method is the decision tree, which shows decision characteristics as nodes, probable results as branches, and classes as leaves. Every decision tree parent node must have a child node. Decision tree algorithms solve classification and regression problems. Splitting the source dataset into successor children creates the decision tree. Classification rules split the dataset. Decision tree algorithms' drawbacks include data overfitting and node overlapping
- Logistic regression: It classifies example data into two classes using supervised machine learning. It uses probability distributions to classify categorical outputs. The likelihood of an outcome is determined by a simple distribution function, which in this case describes the correlation between a single binary dependent variable and a set of independent variables with varying degrees of ordinality, interval size, or ratio. Probability distribution values ranging from 0 to 1, which can be used to classify data

- SVM: It is a common statistical learning concept-based supervised ML technique that uses an optimal separating hyperplane for classification and regression. Support vectors are hyperplane-defining training data. Image, numerical and text classification and regression applications used SVM. It uses various kernel mathematical functions to process data. Most kernel functions are linear, nonlinear, polynomial, or sigmoid. SVM training on massive datasets takes longer than other ML algorithms. It efficiently handles non-linear data using kernel functions. However, selecting a kernel function for the application is difficult

1.6.2 Deep Learning

One of the most effective artificial intelligence techniques for computer vision difficulties is the Deep Convolutional Neural Network (DCNN). As a feed-forward ANN, the DCNN was a type of DL and used in many works to classify images from agriculture (Lu et al. 2021). DCNN relies heavily on the convolutional layer, which applies filters to input images to extract relevant features. To improve DCNN's efficiency, a sizable amount of training data is required.

One of the main benefits of using DCNN to classify images is that it reduces the need for the feature engineering process. DCNN has multiple layers where convolutions are performed. Beginning with broad, overarching representations of the training data at the outermost layers, these layers gradually hone in on increasingly precise details as they travel within the network.

Low-level features are transformed into more useful characteristics for classification by the convolutional layers. In addition, DCNN's initial building blocks are the convolutional layers. Downsampling in the spatial dimension is performed by the pooling layer. It allows for fewer parameters to be used. Maximum pooling is used in the proposed model's pooling layer. Maximum pooling beats average pooling in the proposed DCNN model. Dropout, or the process of removing nodes from a network, is another crucial layer. It is a regularization method that helps lessen the effects of overfitting. In order to train and test the proposed model, dropout values between 0.2 and 0.8 were employed.

After collecting input from the convolutional and pooling layers, the dense layer performs the classification. DCNN must repeatedly train multiple models until the optimum one is found. Using complete training data at each stage, gradient descent (sometimes called batch gradient descent) is a straightforward method for optimising a system. When working with a large training set, gradient descent becomes more of a technical challenge. Fig 1.20 depicts a sample DCNN's layered design for leaf disease detection. This multi-tiered diagram was generated in Python using the Keras framework.

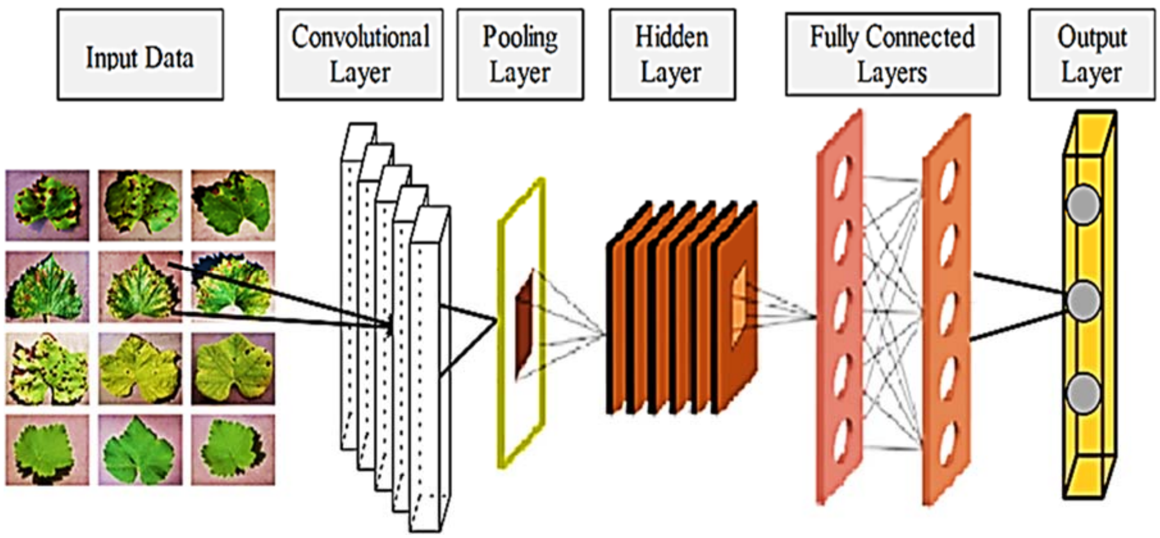

Fig. 1.20 Layered Structure of DCNN for Leaf Disease Detection

1.6.3 Transfer Learning

In machine learning, the concept of "transfer learning" refers to a method for transferring learned information between different models. Initial model creation time is reduced by combining the weights and bias values of existing models. One ML model's output from Task A may serve as input to another ML model's output from Task B.

Transfer learning methods rely on already-trained, state-of-the-art models to glean information from and apply it to new ones. Kaur et al. (2022) include some popular pre-trained DL models, including AlexNet, VGGNet, Residual Network (ResNet), and Inception Network (InceptionNet). The AlexNet is a common pre-trained model of DCNNs. The AlexNet architecture consists of five Rectified Linear Unit (ReLU)-activated convolutional layers and three Fully-Connected (FC) layers. The AlexNet has 62,000,000 trainable parameters. A simplified version of the transfer learning procedure in agriculture is shown in Fig 1.21. VGGNet outperforms AlexNet and requires less time to train. The VGGNet uses a smaller kernel size for its convolutional and pooling layers than the AlexNet does, which is a major distinction between the two networks. During training the size of thec kernel does not change.

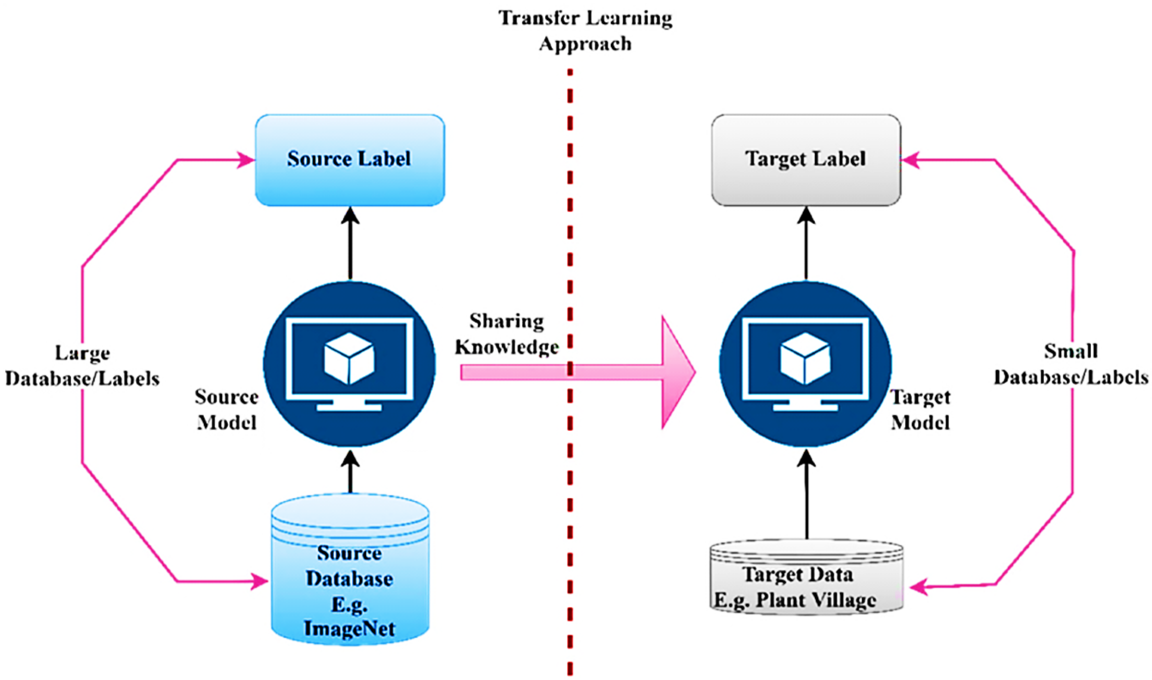

Fig. 1.21 Example of Transfer Learning in Agriculture

The VGG16 and VGG19 VGGNet variants are two examples. These networks can be trained with a total of 138,000,000 parameters. When training DCNNs, the ResNet is used to solve the vanishing gradient issue. It makes use of a direct link to improve the performance of the whole network. Two pooling layers are all that make up this network. Even more common than ResNet18 and ResNet101, however, are ResNet50 and ResNet101. There are 11 million trainable parameters in the ResNet18. The InceptionNet provides parallel kernel methods to handle a wide range of kernel parameters. The GoogleNet is a very basic type of the InceptionNet. GoogleNet can have as many as 6.4 million trainable parameters.

1.6.4 Data Augmentation

Data augmentation is often used when a larger dataset is desired. Using image modifications to introduce a limited number of deliberately distorted pictures into the training set may help prevent overfitting. For image classification tasks with low data quality, data augmentation is the most common solution. Using various methods of transformation, data augmentation creates new pictures.

Optional enhancements include Principal Component Analysis (PCA), Principal Adversarial Networks (PANs), and Neural Style Transfer (NST), in addition to the standard four colour and seven position enhancements. Alterations such as affine transformations, scaling, cropping, flipping, padding, rotation, and translation may be used to fine-tune the placement. Lightness, contrast, saturation, and hue are the four most common ways to alter colour quality. The GAN is only one kind of unsupervised neural network that may be used to generate a fresh collection of realistic images (Dhaka et al., 2021).

The generator network and the discriminator network make up the GAN. The generator network generates novel images that are similar to the training data, and the discriminator network classifies both the original image and the created image. One of the most effective image enhancement methods in the field of image processing is GAN. The NST is a method for creating new pictures by combining three existing ones—the "input," "style reference," and "content" images.

1.6.5 Hyperparameter Optimization

The hyperparameters of a ML algorithm are the most crucial limitation during its training phase. Important hyper-parameters include epochs, mini-batch sizes, and dropout probabilities. The selection of appropriate hyperparameters is the DCNN design's most crucial step. Because of this, the model's precision may drop. Hyperparameters have a major impact on the outcome of AI model training. Common DCNN hyper-parameters include the learning rate, number of epochs, filter and batch size, loss function, dropout rates, and activation functions. One of the most difficult parts of developing the AI model is choosing appropriate values for the hyperparameters.

To maximize performance, hyperparameters tuning is used to determine optimal values for the hyperparameters. One common method for adjusting the AI model's parameters is the random grid search method. To train the model and determine a score, the random grid search generates a grid of possible hyperparameter values and randomly selects combinations from the grid (Subramanian et al. 2022). The number of possible permutations of the parameters can be limited in this way. Time or available resources determine the maximum number of search iterations.

1.7 MOTIVATION OF THE RESEARCH

Low agricultural output is a result of a number of factors, including but not limited to: soil nutrient depletion and pest-borne illnesses; irrigation difficulties; soil erosion; a lack of storage space; a lack of quality seeds; a lack of transportation; ineffective marketing; and so on. Predicting the spread of illnesses is one of the many obstacles yet to be overcome in the agricultural industry. Disease detection in farming has traditionally relied on visual examination, a method that requires skill and expertise. The goal of this study is to automate the visual inspection process of detecting and identifying. Because most plant illnesses manifest in the leaves, this is made feasible by having access to photographs of the plant or portions of plants. It reveals, without a doubt, the need for a unified pest and leaf disease categorization model and a recommendation system for farmers to advise appropriate pesticides to manage pests and leaf diseases, therefore greatly improving crop quality. This is the driving force for the proposed study, which seeks to build and create a deep-learning model for plant leaf disease and pest detection and pesticide prescription.

1.8 PROBLEM STATEMENT

The problems considered for the proposed research work are the following:

- Diseases affected only part of the leaf or the whole. Thus, the spatial correlations across a series of image samples need to be learned for boosting the performance of high-resolution leaf image generation using adversarial network
- The adversarial training objectives like mean squared error to fine-tune the generator network for high-resolution leaf image generation can have non-convergent limit cycles near equilibrium
- Plant pests and diseases have historically played a significant role in determining the level of overall crop yield. In addition, climate change and other climatic conditions are crucial to the plant's development.

- The prediction model should be developed in such a way that it can forecast the pesticide for pest and disease control

1.9 OBJECTIVES OF THE RESEARCH

The primary goal of this study is to use DL algorithms to create a reliable model for identifying plant leaf diseases, pests, and recommending appropriate pesticides. Components of the overall project objectives include,

- To address the problem of learning the spatial relationships across a series of plant leaf images about the observations of diseases affected parts
- To address the issue of weaknesses of adversarial learning ability to create high-resolution plant leaf images
- To address the issue of identifying relationship between a set of pests and leaf diseases using hybrid models
- To address the issue of recommending pesticides using hybrid fuzzy approximation-based decision support system

1.10 RESEARCH CONTRIBUTION

The research work proposes different sub-units for leaf disease, pest detection and pesticide recommendation. These are including:

- A Positional-aware Dual-Attention and Topology-Fusion with Generative Adversarial Network (PDATFGAN) for high-resolution leaf image generation and DCNN for leaf disease classification
- A Positional-aware Dual-Attention and Topology-Fusion with Evolutionary Generative Adversarial Network (PDATFEGAN) and DCNN for leaf disease classification
- A Multi-dimensional Feature Learning-based DCNN (MFL-DCNN) for leaf disease and pest classification
- Hybrid Rough Set with intuitionistic Fuzzy approximation space (RSF)-based decision support system for pesticide recommendation

1.11 ORGANIZATION OF THE THESIS

The thesis sections are organized as follows:

Chapter 1 presents an overview of leaf diseases, pest control strategies, leaf disease and pest detection in agriculture, digital image processing in agriculture and AI models in agriculture. The thesis's motivation and its stated objectives for the study are also discussed.

Chapter 2 Describes a comprehensive literature review on the use of AI models for pest identification and pesticide prescription in agriculture, as well as image processing using ML models for disease detection in leaves.

Chapter 3 elucidates the research methodology, scope of the research, experimental setup and performance metrics.

Chapter 4 describes the first contribution of the research such as the PDATFGAN to enhance the high-resolution leaf image generation for leaf disease detection. Comparisons are made between the proposed model's performance and that of current models.

Chapter 5 explains the second contribution of the research called the PDATFEGAN to optimize the adversarial learning for high-resolution leaf image generation and leaf disease detection. A comparison of quality analysis for proposed and existing models is also presented.

Chapter 6 focuses on the study's third contribution, which includes the MFL-DCNN, which uses multi-dimensional characteristics to identify leaf diseases and pests in tandem. The suggested model's performance is also compared to that of similar models.

Chapter 7 emphasizes the RSF-based recommendation system for helping farmers choose effective pesticides and manage leaf diseases, the study's fourth major contribution. In addition, a comparison of the suggested model's performance with that of current models is provided.

Chapter 8 describes how the quality of the proposed works was assessed using cutting-edge techniques.

Chapter 9 concludes the thesis with the major findings of the study. Also, the possible future extensions to this study are outlined.

Several authors' publications are cited as examples of the study done to back up the claims made in the thesis. The thesis includes a reference section where all sources utilized are identified.

1.12 SUMMARY

In this chapter, an overview of agriculture in India, factors influencing plant diseases, different kinds of leaf diseases and pests, pest control strategies, digital image processing in agriculture, especially for leaf disease detection, applications of AI models in agriculture and open datasets for leaf diseases and pest detection are briefly discussed. The motivation, scope, objectives and contributions of this research are presented. A summary of the organization of the chapters, which appear in the thesis, is also given.