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OPTION: Plant Production

Topic

Application of artificial intelligence in plant protection

Presented by:

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Abbes Laghrour University

Dedication

Firstly, we thank the **Almighty God**, for the guidance, strength, power of mind, protection and skills and for giving us a healthy life.

This study is whole heartedly dedicated to our **beloved parents**, who have been our source of inspiration and gave us strength when we thought of giving up, who continually provide their moral, spiritual, emotional, and financial support.

To our **brothers**, **sisters**, **relatives**, **mentor**, **friends**, and **classmates** who shared their words of advice and encouragement to finish this study.

عنوان المذكرة : تطبيق الذكاء الاصطناعي في مجال وقاية النباتات

الإسم و اللقب : محمد رياض شخار و أكرم جعرير

المؤطر : سليم لبعل

ملخص

تقدم هذه الرسالة الجامعية تطوير وتنفيذ تطبيق ويب مصمم لاكتشاف أمراض أوراق التفاح، وخاصة جرب التفاح، الصدأ، وعفن التفاح الأسود. يستفيد التطبيق من تقنيات التعلم الآلي المتقدمة، وبالأخص الشبكات العصبية الالتفافية(CNNs) ، للتعرف بدقة على هذه الأمراض الشائعة وتصنيفها من الصور التي يتم تحميلها. يتميز النظام بواجهة سهلة الاستخدام تتيح لمزارعي التفاح والمتخصصين في الزراعة تحميل صور أوراق التفاح والحصول على نتائج التشخيص في الوقت الفعلي.

تشمل مراحل البحث عدة جوانب رئيسية: جمع البيانات، تدريب النموذج، تطوير التطبيق، وتقييم الأداء. تم تجميع مجموعة بيانات شاملة تضم صورًا مصنفة لأوراق التفاح السليمة والمصابة من قواعد بيانات زراعية مختلفة ومصادر ميدانية. تم تدريب نموذج الشبكة العصبية الالتفافية وضبطه باستخدام هذه المجموعة، محققًا دقة عالية في اكتشاف الأمراض وتصنيفها.

تم تطوير تطبيق الويب باستخدام تقنيات الويب الحديثة، مما يضمن الوصول إليه واستجابته عبر مختلف الأجهزة. تم تنفيذ خدمات الخلفية لمعالجة الصور، واستنتاجات النموذج، وتوصيل النتائج بكفاءة. تم اختبار أداء التطبيق بدقة في ظروف العالم الحقيقي، مما يظهر إمكانياته كأداة قيمة للكشف المبكر عن الأمراض وإدارتها في بساتين التفاح.

تساهم هذه الرسالة في مجال الزراعة الدقيقة من خلال توفير حل عملي للكشف المبكر عن أمراض أوراق التفاح، مما يمكن أن يقلل بشكل كبير من خسائر المحاصيل ويحسن جودة الإنتاج. يمكن أن يركز العمل المستقبلي على توسيع نطاق الأمراض القابلة للكشف، وتعزيز دقة النموذج، ودمج ميزات إضافية مثل تقييم شدة المرض.

الكلمات المفتاحية: تطبيق ويب، الذكاء الاصطناعي، (CNN)، الكشف، التشخيص، التفاح.

Titre du mémoire : Application de l'intelligence artificielle dans le domaine de la protection des végétaux

Nom et prénom : CHAKHAR Mohamed Rayad & DJAARIR Akram

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Résumé

Ce mémoire de master présente le développement et la mise en œuvre d'une application web conçue pour détecter les maladies des feuilles de pommier, notamment la tavelure, la rouille et la pourriture noire du pommier. L'application utilise des techniques avancées d'apprentissage automatique, en particulier les réseaux neuronaux convolutifs (CNN), pour identifier et classer avec précision ces maladies courantes des feuilles de pommier à partir d'images téléchargées. Le système est doté d'une interface conviviale qui permet aux producteurs de pommes et aux professionnels de l'agriculture de télécharger facilement des images de feuilles de pommier et de recevoir des résultats diagnostiques en temps réel. La recherche implique plusieurs étapes clés : la collecte de données, l'entraînement du modèle, le développement de l'application et l'évaluation des performances. Un ensemble de données complet comprenant des images étiquetées de feuilles de pommier saines et malades a été assemblé à partir de diverses bases de données agricoles et sources sur le terrain. Le modèle CNN a été entraîné et affiné en utilisant cet ensemble de données, atteignant une grande précision dans la détection et la classification des maladies. L'application web a été développée en utilisant des technologies web modernes, garantissant l'accessibilité et la réactivité sur différents appareils. Des services back-end ont été mis en œuvre pour gérer le traitement des images, l'inférence du modèle et la livraison des résultats de manière efficace. Les performances de l'application ont été rigoureusement testées dans des conditions réelles, démontrant son potentiel en tant qu'outil précieux pour la détection précoce des maladies et la gestion dans les vergers de pommiers. Ce travail contribue au domaine de l'agriculture de précision en fournissant une solution pratique pour la détection précoce des maladies des feuilles de pommier, ce qui peut réduire considérablement les pertes de récoltes et améliorer la qualité des rendements. Les travaux futurs pourraient se concentrer sur l'élargissement de la gamme de maladies détectables, l'amélioration de la précision du modèle et l'intégration de fonctionnalités supplémentaires telles que l'évaluation de la gravité des maladies.

Mots-clés : Application web, Intelligence artificielle, (CNN), Détection, Diagnostic, Pomme.

Title of the dissertation: Application of artificial intelligence in plant protection

Full name: CHAKHAR Mohamed Rayad & DJAARIR Akram

Directed by: Salim LEBBAL

Abstract

This master's dissertation presents the development and implementation of a web application designed to detect apple leaf diseases, specifically apple scab, rust, and apple black-rot. The application leverages state-of-the-art machine learning techniques, particularly convolutional neural networks (CNNs), to accurately identify and classify these common apple leaf diseases from uploaded images. The system is built with a user-friendly interface that allows apple growers and agricultural professionals to easily upload images of apple leaves and receive real-time diagnostic results.

The research involves several key stages: dataset collection, model training, application development, and performance evaluation. A comprehensive dataset comprising labeled images of healthy and diseased apple leaves was assembled from various agricultural databases and field sources. The CNN model was trained and fine-tuned using this dataset, achieving high accuracy in disease detection and classification. The web application was developed using modern web technologies, ensuring accessibility and responsiveness across different devices. Backend services were implemented to handle image processing, model inference, and result delivery efficiently. The performance of the application was rigorously tested under real-world conditions, demonstrating its potential as a valuable tool for early disease detection and management in apple orchards.

This work contributes to the field of precision agriculture by providing a practical solution for early detection of apple leaf diseases, which can significantly reduce crop losses and improve yield quality. Future work may focus on expanding the range of detectable diseases, enhancing the model's accuracy, and integrating additional features such as disease severity assessment.

Keywords: Web application, Artificial intelligence, (CNN), Detection, Diagnostic, Apple.

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List of abbreviations

AI : Artificial intelligence

ANN : Artificial Neuron Network

CNN : Convolutional Neural Network

DL : Deep Learning

F.A.O : Food and Agriculture Organization

FC : Fully Connected

GAP : Global Average Pooling

i.e : id est

ML : Machine Learning

RGB : Red-Green-Blue

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Introduction

Malus pumila Mill. Has long been the cultivated apple tree. However, it is highly likely that the apple tree originated from the Caucasus and the shores of the Caspian Sea. From these regions, its cultivation spread to Eastern Europe, Russia, and eventually Western Europe. Despite uncertainty regarding the precise origin of the contemporary apple, it is also probable that it evolved from extensive forests of apple trees in Central Asia, particularly in Kazakhstan. This species is also present in the region stretching from the Balkans to the northern Altai Mountains. Today, it is cultivated in countries across the globe, spanning latitudes from 25° to 60° North and in the Southern Hemisphere, including New Zealand, Australia, Southern Africa, Argentina, Chile, and Southern Brazil, among others (Lespinasse & Gallis, 1990 cited by Gallais & Hubert, 1992).

Since independence, Algeria, like other countries worldwide, has been striving to halt the importation of this fruit by effectively managing orchards, improving production, and increasing yields (Soltani, 1998). In 2022, there were 32071 hectares of apple orchards (F.A.O, 2024), mainly located in Médéa, Batna, Tiaret, Blida, and Khenchela. During the same year, apple production in Algeria amounted to 539852,35 tons, with a yield of 168,3 Qx/ha. However, this yield remains significantly lower compared to some countries (F.A.O, 2024)

According to the Direction of Agricultural Services (DSA), the province of Khenchela has been the leader in the apple cultivation sector, with a production of 1.6 million quintals during the agricultural season 2022-2023. In this region,there are 6,000 hectares of apple orchards, primarily located in the communes of Bouhmama, M'sara, Yabous, Chelia, Khirane, Taouzianet, Remila, Tamza, Kaïs, Ensigha and Babar. These orchards boast a wide range of different varieties, including Golden Delicious (62% of production), Top Red (17%), Royal Gala (16%), Starkrimson (5%), and others (D. FATEN).

Worldwide, apples are subject to numerous diseases caused by pathogenic fungi, bacteria, oomycetes, and viruses. Diverse fungal diseases include root rots, leafs pots, leaf blights, blossom blights, fruit decay, fruits pots, defoliation, trunk, branch, and twig cankers (Grove et al., 2003). Apples cab, caused by *Venturia inaequalis*, is considerably one of the most important diseases of apples worldwide (MacHardy, 1996).

Oomycetes, *Phytophthora spp*., causing crown and root rot, are serious soil-borne diseases associated with moist soil conditions and may be responsible for tree death (Jackson & Palmer, 1999). Powdery mildew, caused by *Podosphaera leucotricha*, is also common in all apple-producing nations. Bacterial diseases such as fire blight, blister spot, blister bark, crown gall, and hairy root affect apple (Grove et al., 2003). Fire blight, caused by *Erwinia amylovora*, is a serious bacterial disease that affects the entire tree and can lead to significant tree loss (Grove et al., 2003).

Artificial intelligence (AI) has grown exponentially in recent years in many areas, including agriculture. In the specific area of apple branch disease detection, AI is essential for improving the health of fruit trees, optimizing yields, and ensuring crop quality. As part of the optimization of apple yield and harvest quality, as well as with the aim of ensuring food security for consumers, an innovative approach has been developed. This approach is based on an integration of agronomic expertise focused on apple production and cutting-edge technologies such as artificial intelligence (González-Rodríguez et al, 2024).

The objective of the present project is to develop an application that leverages advanced technologies for the identification and classification of apple tree diseases through the scanning of symptoms visible on the leaves. This application will analyze images of the leaves to detect signs of diseases and provide accurate diagnostics. Additionally, it will offer tailored solutions for both biological and chemical control, recommending approved phytosanitary products. Thus, this approach aims to provide farmers with an effective and reliable tool to manage the health of their crops and optimize their production.

Chapter one: Apple Diseases

Chapter 1: Apple Diseases

1.1 Diseases Caused by Bacteria

1.1.1 Fire Blight

The fire blight pathogen kills fruit-bearing spurs, branches and entire trees. Infected blossoms are initially water-soaked and darker green; spurs with infected blossoms turn brown to dark brown and collapse after 4–5 days. Infected shoots turn brown to black from the tip and bend near the tip to resemble a shepherd's crook. When shoots are invaded from the base, the basal leaves and stem turn brown to black. Leaves may exhibit discoloration of the midrib, followed shortly by a darkening of the lateral veins and surrounding tissues. Bark on infected branches and scaffold limbs are darker than normal. When the outer bark is peeled away, the inner tissues are water-soaked with reddish streaks when first invaded; later the tissues are brown. As lesion expansion slows, the bark sometimes cracks, delineating a canker. Infected fruit develop a brown-to-black decay. During wet, humid weather, droplets of whitish to reddish-brown, sticky liquid (known as ooze) seeps from the surface of infected tissues. Infected rootstocks may show bleeding or ooze from rootstock tissue early in summer and internal necrosis of the bark and the leaves of the scion turn reddish early in the autumn.

Figure 1. Fire blight on apple shoot (Smith, 2017)

Fire blight is caused by *Erwinia amylovora* (Burrill) Winslow et al., a Gram-negative, rod-shaped, non-fluorescent bacterium with peritrichous flagella. More than 130 species in 39 genera of the Rosaceae are hosts. Important hosts include apple, pear, ornamental *Pyrus* and *Malus* species, quince (*Cydonia oblonga*), loquat (*Eriobotrya* *japonica*), hawthorn (*Crataegus spp.*), *Cotoneaster spp*., *Sorbus spp*., *Pyracantha spp*. and *Rubus spp*.

The pathogen overwinters in cankers located on branches and tree trunks (Figure 2).

The susceptible rootstocks M.9 and M.26 are infected by systemic movement of bacteria through symptomless scion tissue or through infected rootstock shoots (Momol et al., 1998). Although the rootstock Bud.9 is blight-susceptible, rootstock blight has not developed on many Bud.9/scion combinations.

Many practices help to prevent or reduce the severity of fire blight. In countries where *E. amylovora* is not established, only trees produced in fire-blight-free regions should be used when establishing new orchards. These countries may already have strict quarantines to prevent the importation of plant material that may harbour the pathogen. In countries where fire blight is a problem, sanitation – the removal of infected portions of the tree – is critical to the success of other control measures and is effective provided it is done during the early stages of an epidemic. New orchards should be planted on blight-resistant rootstocks if available (Curtis & Ian, 2003).

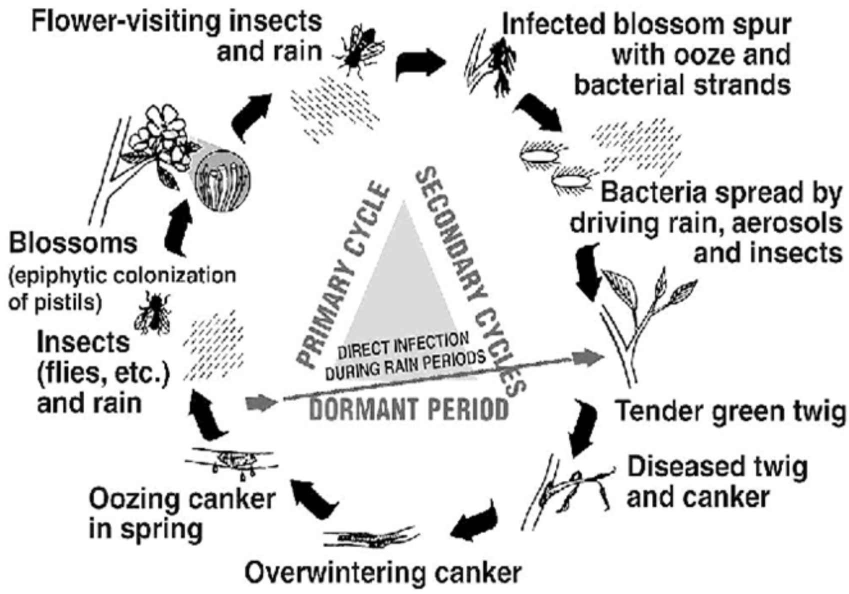

Figure 2. The fire blight disease cycle (Grove et al, 2003).

1.2 Diseases Caused by Fungi

1.2.1 Moniliosis

The brown-rot fungi cause blossom wilt, spur dieback, cankering and fruit rot; the incidence and severity of these symptoms depend on the species of pathogen present.

Monilinia laxa causes blossom blight, spur dieback and cankering of branches; *M. fructigena* causes fruit rot and sometimes cankers when the fungus spreads into branches from the fruit; and *M. fructicola* causes a fruit rot. *Monilia* leaf blight infects young apple leaves; mycelium invading from leaves kills flower clusters, young fruits and fruiting spurs.

Figure 3. Mummified apples due to moniliosis (Chaillot, 2023)

Infection also occurs through wounds caused by birds pecking at fruit, insects infesting fruit and hail. Fruit decay is prevented by avoiding cultivars prone to fruit cracking, by limiting the damage caused by birds and other wounding agents and by orchard sanitation methods aimed at reducing the build-up of inoculum. Blossom infections from *M. laxa*, *M. fructigena* and *Monilia* leaf blight are controlled by orchard sanitation, combined with the application of fungicides. Blighted spurs and cankers are removed and destroyed during the dormant period and in the growing sea-son. Fungicides applied as the flowers begin to open and one or two times 5–7 days later should prevent blossom blight (Curtis & Ian, 2003).

1.2.2 Topaz Spot

Apple anthracnose caused by *Elsinoë pyri* (Classification: *Fungi, Ascomycota, Pezizo mycotina, Dothideomycetes, Dothideomycetidae, Myriangiales, Elsinoaceae*) was once considered a rare disease, occurring in apple orchards with low fungicide coverage. It is considered a secondary disease, but can render fruit unmarketable (INRA, 2016).

Figure 4. Typical symptoms of *Elsinoe pyri* on fruit and leaves of apple (Korsgaard et al, 2014).

On adult leaves, small, round, light-green spots 2 to 3 mm in diameter can be seen from the end of June. They quickly turn grayish, then whitish, with a clear brown-black outline. On fruit, the disease first appears in the form of small, round spots, 1 to 3 mm in diameter, with sharp, pinkish-grey outlines. The central part of the spot turns white, while the periphery turns dark brown. On colored fruit, a dark red edge may be added. These symptoms only affect the skin of the fruit, but do not affect its taste or yield. However, the appearance makes the crop unmarketable. *Elsinoë pyri* is found in orchards with little or no treatment. In at-risk plots, a copper-based treatment is recommended in June (Lemoine, 1998 cited by CTIFL, 2018).

1.2.3 Powdery Mildew

Powdery mildew of apple, caused by the fungus *Podosphaera leucotricha*, occurs in all major apple-growing areas of the world, especially in semiarid regions. The fungus infects apples, flowering crab apples, and pears. Losses from the disease vary depending on susceptibility of the cultivar, environmental conditions, and management practices.

Powdery mildew of apple produces symptoms on blossoms, young shoots, leaves, and fruit. In general, symptoms are most noticeable on the leaves and fruit.

- *Leaves* are colonized as they emerge from the buds. White fungal colonies develop on leaves. Lesions first appear as whitish, felt-like patches of fungal mycelium and spores on the undersides and along the margins. The lesions spread rapidly and may cover the entire leaf. Infected leaves are narrower than normal, are folded longitudinally, and become stiff and brittle with age (Figure 5).

Figure 5. Apple powdery mildew leaf damage (Profert, 2024)

- *Fruits* are rarely infected, unless the disease is built up to high levels. Infected fruit are rusted and sometimes stunted.

The life cycle of *P. leucotricha* is described in the Figure 6.

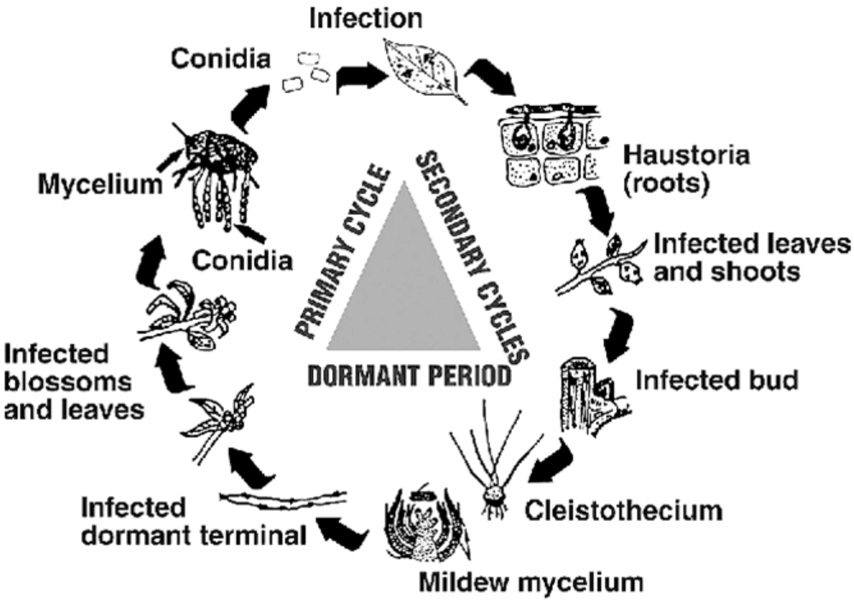

Figure 6. The apple powdery mildew disease cycle (Grove et al, 2003).

The fungus overwinters as mycelium in infected buds. Mildew conidia, produced on leaves arising from the infected buds, become wind-borne and cause primary infections on healthy leaves and fruit.

The disease management can be divided into:

- **Cultivar Selection:** The use of less susceptible apple cultivars is an effective way of preventing mildew. Some mildew resistant cultivars include Enterprise, Jonafree, Prima, and Winsap. Cultivar selection is influenced more by commercial appeal, fruit qualities, marketability, and pollination characteristics than by disease resistance.

- Cultural Practices: Primary infections can be controlled by removal of the primary inoculum sources (i.e., flower and shoot buds infected the previous year). Growers should note any whitened terminal shoots and prune them out during winter or early spring. Unfortunately, complete removal of this type of inoculum is just not economically feasible. The best candidates to use this control practice are small young orchards with low numbers of primary infections per tree.

- Chemical Management: Where susceptible cultivars are grown, mildewcide should be included in the scab program to provide control of both diseases. Begin sprays at tight cluster and continue until terminal growth stops. Early spray (tight cluster to petal fall) are essential to success in management of powdery mildew (Marine, 2010)

1.2.4 Apple Scab

The disease is an annual threat in cool, humid regions with frequent rainfall in spring and early summer. In semiarid regions, scab is a threat in years with above-normal rainfall or in orchards where artificial wetting periods are created from the improper use of over-head irrigation.

Figure 7. Apple scab on fruit (Koetter & Grabowski, 2024)

Figure 7 shows an apple fruit affected by apple scab, caused by the fungus *Venturia inaequalis*. The disease results in dark, scabby lesions on the fruit's surface.

Scab attacks the leaves and fruit throughout most of the growing season; blossoms and bud scales are attacked for short periods in spring and late summer, respectively. Symptoms first appear on the undersides of leaves, the side exposed as buds open. Later, symptoms are found on both sides of leaves. Conidia are produced abundantly in new lesions; therefore, lesions appear as velvety brown to olive spots that turn black with age. Severe infection can cause leaves to abscise, resulting in defoliated trees. Return bloom on trees defoliated in midsummer is often reduced due to a lack of flower-bud formation the previous summer. Fruit infections resemble leaf infections when young but turn brown and corky with age.

Venturia inaequalis (Cooke) G. Wint., anamorph *Spilocea pome* Fr., causes apple scab. It has one sexual cycle and a series of asexual cycles per year. Flask-shaped, ascus-bearing fruiting bodies (pseudothecia) develop in overwintering infected leaves.

The life cycle of *V. iaequalis* is described in the Figure 8.

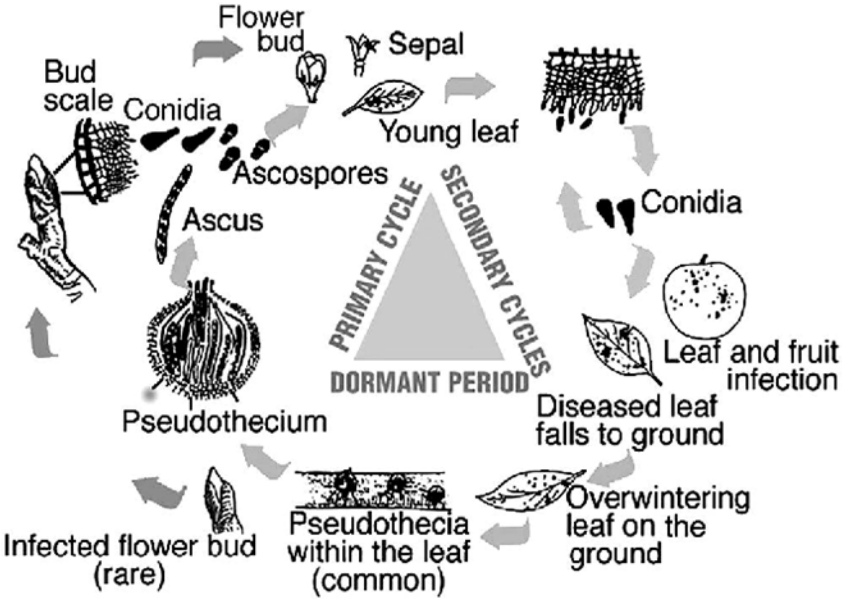

Figure 8. The apple scab disease cycle (Grove et al, 2003)

The fungus *Venturia inaequalis* overwinters in leaves on the orchard floor and sometimes in apple buds. Pseudothecia with ascospore-bearing asci in dead leaves discharge their ascospores when the leaves become wet.

Apple-breeding programmes aiming for high-quality, disease-resistant cultivars are in progress in New Zealand and some European and North American countries. Over 50 scab-resistant cultivars have been released and are gaining in commercial acceptance as fruit quality and other horticultural characteristics are improved. Guarding against races of the scab pathogen that can overcome the resistance sources used by apple breeders is a high priority in these breeding programmes (Bénaouf & Parisi, 2000).

Prevention of pseudothecia formation in overwintering leaves would probably eliminate scab. Unfortunately, complete elimination of pseudothecia is not possible under orchard conditions using current methods. Spring ascospore production can be reduced by making autumn applications of urea or fungal antagonists to the foliage just prior to leaf fall (Carisse et al., 2000), but this strategy alone is not adequate for season-long scab control. This approach may be more feasible in areas with lower amounts of overwintering inoculum and mild winters.

Scab is controlled primarily with fungicides applied in predetermined schedules, beginning at green tip. The fungicides are applied on a 7–14-day interval with eight to ten applications per season. Several classes of fungicides are available for apple-scab control. They are often rotated during the season or applied as mixtures because of the high potential of the scab fungus to develop fungicide-resistant strains (Curtis & Ian, 2003).

1.3 Conclusion

Apple trees are vulnerable to various diseases that can affect their leaves, stems, and branches. It is crucial to implement preventive and control measures to mitigate the impact of these diseases. This involves adopting good cultural practices such as pruning and removing infected tissues, using recommended fungicides or bactericides, and creating a healthy environment for apple trees. Regular tree monitoring and consulting with arboriculture experts can also help prevent the spread and severity of these diseases.

Chapter two: Use of Artificial Intelligence in agriculture

Chapter 2: Use of Artificial Intelligence in agriculture

2.1 Introduction

As the global population grows, it is essential to review agricultural practices and introduce innovative approaches to sustain and improve agricultural activities. The introduction of AI in agriculture will be enabled by technological advances such as big data analytics, robotics, internet of things, cheap sensors, cameras, drone technology, and wide-scale internet coverage on geographically dispersed fields. AI systems can analyze soil management data to provide predictive insights into crop planting and optimal sowing and harvest dates, improving crop yields and reducing the use of water, fertilizers, and pesticides. This application of AI technologies can also reduce the impact on natural ecosystems and increase worker safety (Bannerjee et al, 2018).

2.2 Historic review

1. During the 1950s and 1960s, vision was the main subject of study. The numbers and letters will be recognized using a machine that is inspired by the modeling of a neural network. This is the Rosenblatt perceptron, a neuron classification tool.
2. At the beginning of the 1970s, it was about specialists drawing knowledge from a field, making it a rule, and integrating it into an educational system. Mycin, an expert diagnostic system, is the most famous example of this period.
3. In the 1980s, attempts were made to develop machines capable of learning, i.e., capable of classifying objects. In biology, sequence databases are increasingly numerous. So, we're going to try to create pattern detectors such as promoters, exons, introns, and coding zones. Bioinformatics, as it exists today, was then emerging and evolving rapidly.
4. In the 1990s, computers continued to gain power; they offered the ability to analyze larger amounts of data. Classifiers evolve, such as support vector machines.
5. The 2000s will be marked by the growing emergence of graph data representations.
6. These neural architectures will stand out in the 2010s, solving problems of image recognition and language translation. Nowadays, they are used in the field of medical imaging but are still neglected for the analysis of omics data. The progress just described is due to the increased power of computers, as well as their structures and software environments (Bannerjee et al, 2018).

2.3 Definition of AI

The concept of artificial intelligence (AI) was first used in 1956 at the Dartmouth International Conference in New Hampshire, where scientists began to think that they could recreate the mechanisms of the human brain in machines. The Encyclopaedia Larousse (2021) defines AI as “a set of theories and techniques applied to create machines capable of simulating human intelligence”. Besides, Bertrand Braunschweig (2019) evokes a "program that aims to accomplish, at least as much as human beings, tasks that require a certain level of intelligence (Bannerjee et al, 2018)."

2.4 Deep learning

Deep learning is a subset of machine learning research that has gained popularity in recent years. Deep learning models are a special type of artificial neural network that learns multiple levels of representation by using a hierarchy of multiple layers. The biggest advantage of deep learning techniques is that they do not rely on hand-crafted features. Rather, these networks learn features while training without any human intervention. Recent advances in computer vision made possible by deep learning have paved the way for efficient and reliable visual systems that are extensively used in many areas like autonomous cars, medical image analysis, robotics, etc. In recent years, convolutional neural networks (CNNs), one of the most successful deep learning algorithms, have dramatically achieved great success and won numerous contests in pattern recognition and computer vision. They have shown excellent performance in many computer vision and machine learning tasks like image classification, object detection, speech recognition, natural language processing, medical image analysis, etc. For example, in 2017, Brahimi et al. introduced deep learning as an approach for classifying tomato disease based on leaf images and achieved state-of-the-art results with a classification accuracy reaching up to 99%, easily outperforming the conventional methods (Khana et al, 2021).

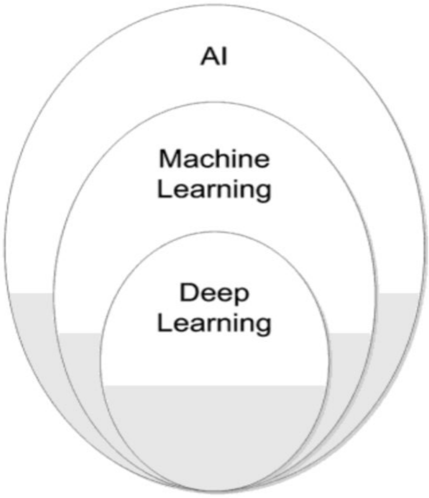

Figure 9. Deep learning is a subset of machine learning which is a subset of AI (Mueller & Massaron, 2019)

This figure is a Venn diagram showing the relationship between Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL). The diagram illustrates that Deep Learning is a subset of Machine Learning, which in turn is a subset of Artificial Intelligence. Here's a breakdown:

- **The outermost** oval represents **AI**, encompassing all systems that mimic human intelligence.
- **The middle oval** represents **Machine Learning**, which is a branch of AI that focuses on systems that learn from data.
- **The innermost oval** represents **Deep Learning**, a subset of Machine Learning that uses neural networks with many layers to analyze various factors of data.

2.5 Image classification

It refers to the classification of various objects in images such as persons, crops, trees, soil, minerals, water bodies, etc. The different objects or regions in the image have to be identified and classified. The classification algorithm determines the accuracy of the result. It is usually based on a single image or sets of images. When sets of images are used, the set will contain multiple images of the same object with different views and under different conditions. It will be more effective in classification when compared to classifying with single images, since the algorithm can accommodate varying conditions like differences in background, illumination, or appearances. It can also be invariant to image rotation and other transformations.

Examples:

- Satellite image is the input for which classification has to be done.
- Problem is to identify or classify the pixels into land, desert, crop coverage, water, mountains, minerals, etc.
- Land cover can be classified into different themes called thematic mapping.
- Supervised learning: information on the relationship between pixel values in different bands and the classes has to be known based on training data.
- Unsupervised learning: information on the relationship between pixel values in different bands and the classes has to be learnt.
- Features: attributes of the pixels that could possibly be numerical values in different bands of a multispectral image (Jude & Vieira, 2017).

2.6 Regularization to CNN

For CNN models, over-fitting represents the central issue associated with obtaining well-behaved generalization. The model is entitled over-fitted in cases where the model executes especially well on training data and does not succeed on test data (unseen data) which is more explained in the latter section. An under-fitted model is the opposite; this case occurs when the model does not learn a sufficient amount from the training data. The model is referred to as "just-fitted" if it executes well on both training and testing data. These three types are illustrated in Fig.10. Various intuitive concepts are used to help the regularization to avoid over-fitting; more details about over-fitting and under-fitting are discussed in latter sections.

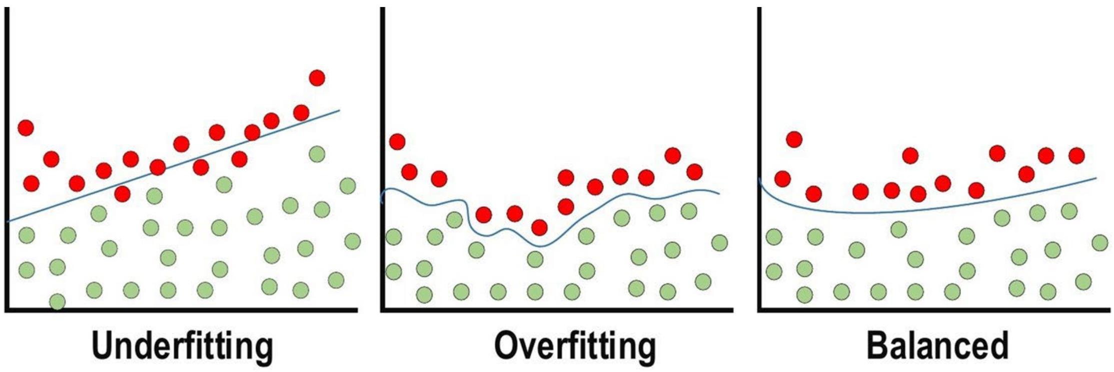

Figure 10. Over-fitting and under-fitting issues (Alzubaidi et al, 2021)

1. **Dropout:** This is a widely utilized technique for generalization. During each training epoch, neurons are randomly dropped. In doing this, the feature selection power is distributed equally across the whole group of neurons, as well as forcing

the model to learn different independent features. During the training process, the dropped neuron will not be a part of back-propagation or forward-propagation. By contrast, the full-scale network is utilized to perform prediction during the testing process.

2. **Batch Normalization:** This method ensures the performance of the output activations. This performance follows a unit Gaussian distribution. Subtracting the mean and dividing by the standard deviation will normalize the output at each layer. While it is possible to consider this as a pre-processing task at each layer in the network, it is also possible to differentiate and to integrate it with other networks. In addition, it is employed to reduce the "internal covariance shift" of the activation layers. In each layer, the variation in the activation distribution defines the internal covariance shift. This shift becomes very high due to the continuous weight updating through training, which may occur if the samples of the training data are gathered from numerous dissimilar sources (for example, day and night images). Thus, the model will consume extra time for convergence, and in turn, the time required for training will also increase. To resolve this issue, a layer representing the operation of batch normalization is applied in the CNN architecture.

The advantages of utilizing batch normalization are as follows:

- It prevents the problem of vanishing gradient from arising.
- It can effectively control the poor weight initialization.
- It significantly reduces the time required for network convergence (for large-scale datasets, this will be extremely useful).
- It struggles to decrease training dependency across hyper-parameters.
- Chances of over-fitting are reduced, since it has a minor influence on regularization (Alzubaidi et al, 2021).

2.7 Convolutional neural network (CNN)

2.7.1 CNN architecture

The CNN architecture consists of a number of layers (or so-called multi-building blocks). Each layer in the CNN architecture, including its function, is described in detail below.

1. **Convolutional Layer:** In CNN architecture, the most significant component is the convolutional layer. It consists of a collection of convolutional filters (so-called kernels). The input image, expressed as N-dimensional metrics, is convolved with these filters to generate the output feature map.

- **Kernel definition:** A grid of discrete numbers or values describes the kernel. Each value is called the kernel weight. Random numbers are assigned to act as the weights of the kernel at the beginning of the CNN training process. In addition, there are several different methods used to initialize the weights. Next, these weights are adjusted at each training era; thus, the kernel learns to extract significant features.
- **Convolutional Operation:** Initially, the CNN input format is described. The vector format is the input of the traditional neural network, while the multi channeled image is the input of the CNN. For instance, single-channel is the format of the gray-scale image, while the RGB image format is three-channeled. To understand the convolutional operation, let us take an example of a 4×4 gray-scale image with a 2×2 random weight-initialized kernels. First, the kernel slides over the whole image horizontally and vertically. In addition, the dot product between the input image and the kernel is determined, where their corresponding values are multiplied and then summed up to create a single scalar value, calculated concurrently. The whole process is then repeated until no further sliding is possible. Note that the calculated dot product values represent the feature map of the output. Figure 11 graphically illustrates the primary calculations executed at each step. In this figure, the light green color represents the 2×2 kernel, while the light blue color represents the similar size area of the input image. Both are multiplied; the end result after summing up the resulting product values (marked in a light orange color) represents an entry value to the output feature map.

However, padding to the input image is not applied in the previous example, while a stride of one (denoted for the selected step-size over all vertical or horizontal locations) is applied to the kernel. Note that it is also possible to use another stride value. In addition, a feature map of lower dimensions is obtained as a result of increasing the stride value.

On the other hand, padding is highly significant to determining border size information related to the input image. By contrast, the border side-features moves carried away very fast. By applying padding, the size of the input image will increase, and in turn, the size of the output feature map will also increase.

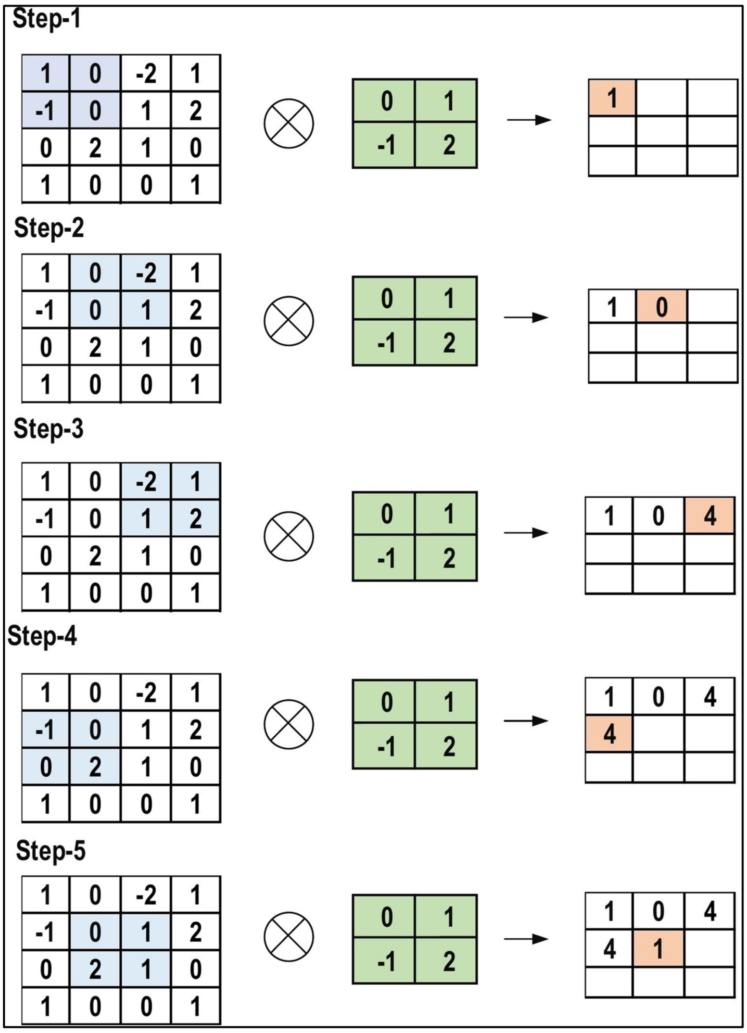

Figure 11. The primary calculations executed at each step of convolutional layer (Alzubaidi et al, 2021).

2.7.2 Sparse Connectivity:

Each neuron of a layer in FC neural networks links with all neurons in the following layer. By contrast, in CNNs, only a few weights are available between two adjacent layers. Thus, the number of required weights or connections is small, while the memory required to store these weights is also small; hence, this approach is memory effective. In addition, matrix operation is computationally much costlier than the dot (.) operation in CNN.

- **Weight Sharing:** There are no allocated weights between any two neurons of neighboring layers in CNN, as the whole weights operate with one and all pixels of the input matrix. Learning a single group of weights for the whole input will significantly decrease the required training time and various costs, as it is not necessary to learn additional weights for each neuron.

2. **Pooling Layer:** The main task of the pooling layer is the sub-sampling of the feature maps. These maps are generated by following the convolutional operations. In other words, this approach shrinks large-size feature maps to create smaller feature maps. Concurrently, it maintains the majority of the dominant information (or features) in every step of the pooling stage. In a similar manner to the convolutional operation, both the stride and the kernel are initially size-assigned before the pooling operation is executed. Several types of pooling methods are available for utilization in various pooling layers. These methods include tree pooling, gated pooling, average pooling, min pooling, max pooling, global average pooling (GAP), and global max pooling. The most familiar and frequently utilized pooling methods are the max, min, and GAP pooling. Figure 12 illustrates these three pooling operations.

Sometimes, the overall CNN performance is decreased as a result; this represents the main shortfall of the pooling layer, as this layer helps the CNN to determine whether or not a certain feature is available in the particular input image, but focuses exclusively on ascertaining the correct location of that feature. Thus, the CNN model misses the relevant information.

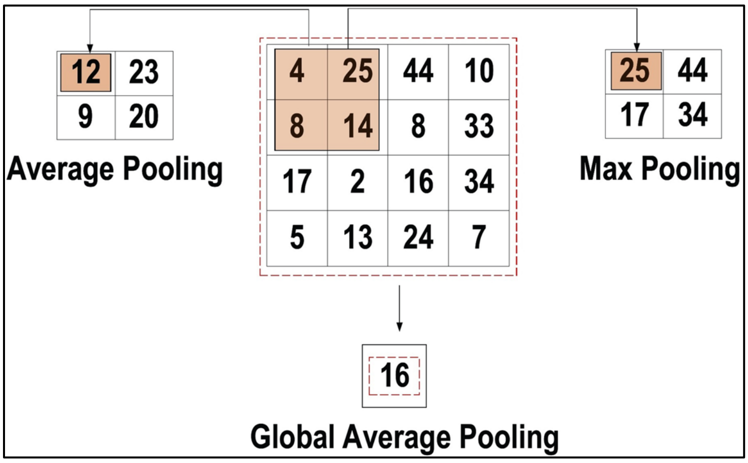

Figure 12. Three types of pooling operations (Alzubaidi et al, 2021).

3. **Fully Connected Layer:** Commonly, this layer is located at the end of each CNN architecture. Inside this layer, each neuron is connected to all neurons of the previous layer, the so-called Fully Connected (FC) approach. It is utilized as the CNN classifier. It follows the basic method of the conventional multiple-layer perceptron neural network, as it is a type of feed-forward ANN. The input of the FC layer comes from the last pooling or convolutional layer. This input is in the form of a vector, which is created from the feature maps after flattening. The output of

the FC layer represents the final CNN output, as illustrated in Fig. 13 *(Alzubaidi et al, 2021)*.

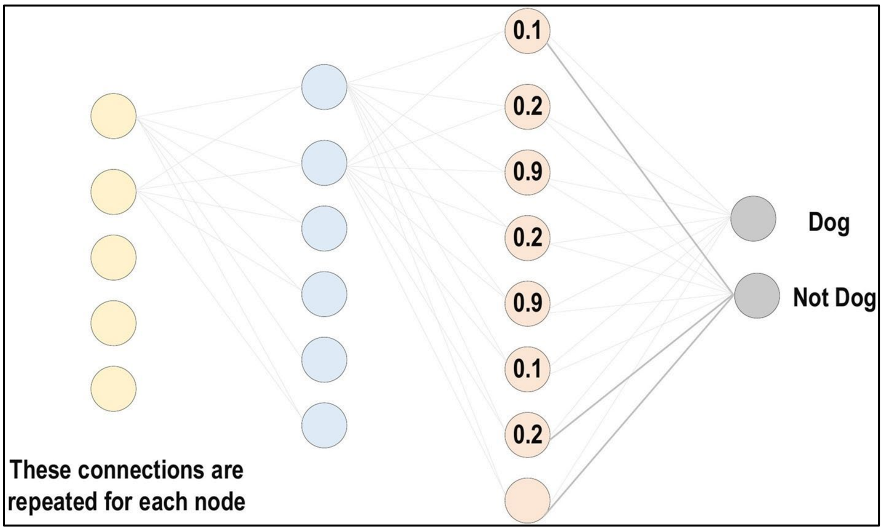

Figure 13. Fully connected layer (Alzubaidi et al, 2021).

2.8 AI in agriculture

Increasing the total agricultural production by 70% in order to meet the world's demand in the next 50 years is an objective endangered by limited resources, climatic changes, and other short-term and regional threats. Despite its relatively short life, artificial intelligence is seen more and more as a solution to these challenges. As the idea that these problems will be surpassed using technology goes forward, some opinions advocate that humanity will merge with AI in the next 50 years, reaching a new phase of evolution (Bannerjee et al, 2018).

2.8.1 Soil and irrigation management

Issues pertaining to soil and irrigation management are very vital in agriculture. Improper irrigation and soil management lead to crop loss and degraded quality. Many researches were carried out in soil and irrigation management assisted by artificially intelligent techniques.

2.8.2 Crop management

The crop management techniques are summarized and starts with sowing and continues with monitoring growth, harvesting, and crop storage and distribution. It is summarized as the activities that improve the growth and yield of agricultural products.

2.8.3 Weed management

The application of herbicides has a direct impact on human health and the environment as well. Modern AI methods are being applied to minimize herbicide application through proper and precise weed management. Pasqual designed a rule-based expert system for identifying and eliminating weeds in crops like oats, barley, triticale, and wheat. Burks et al. used machine vision with a back propagation-trained neural network to identify weeds of five distinct species.

2.8.4 Agricultural product monitoring and storage control

Apart from pests and diseases, monitoring, storage, drying, and grading of harvested crops are also very important aspects of agriculture. Various food monitoring and quality control mechanisms that employ the concept of artificial intelligence.

2.8.5 Pest and disease management

Insect pest infestation is one of the most alarming problems in agriculture and leads to heavy economic losses. Many rule-based expert systems were proposed. Besides, several fuzzy logic-based expert systems were proposed.

On the other hand, computer-aided systems are being used worldwide to diagnose diseases and suggest control measures. At a very early stage, rule-based systems were developed. Furthermore, different artificial neural network-based models were designed for disease control in different crops. Some hybrid systems were also suggested (Bannerjee et al, 2018).

2.9 Conclusion

In conclusion, AI technologies significantly enhance agricultural practices by enabling farmers to analyze land, soil, and crop health efficiently, thus optimizing crop selection and yield for each season. Vertical farming, supported by AI, reduces water consumption, maximizes land use, and facilitates urban cultivation, addressing labor shortages. Additionally, AI-driven predictions of crop seasons, weather, climate, and rainfall allow for timely and precise recommendations for pesticides, crops, and locations, preventing large-scale disease outbreaks.

Chapter three: Web applications in the field of agriculture

Chapter 3: Web applications in the field of agriculture

3.1 Introduction

Mobile applications have become very popular in recent years, and smartphone users continue to increase annually (Bankmycell, 2022). The smartphone market has had several operating systems in the last decade, like BlackBerry, Symbian, Windows Mobile, Windows Phone, Android, and iOS. Some of those, including Symbian and Microsoft Windows Mobile, are discontinued. Apple's iOS and Google's Android dominate the mobile operating system market share, with over 99 percent of the global market in the last decade (Statista, 2022 cited by Parsa, 2023).

Mobile agricultural apps target the needs of the agricultural sector and its stakeholders, such as farmers, agricultural businesses, and cooperatives. These apps cover a spectrum of activities, from cultivation techniques to the agricultural market, offering services such as weather forecasting, agricultural business news, information for agricultural machinery and equipment, agricultural product market prices, management of agricultural products, dairy farming, irrigation systems, crop sensors, yield forecasting and monitoring, soil type registration, and calculation (Costopoulou et al, 2016).

3.2 Definition and generalities

A web application is software that runs on the web. Unlike the typical desktop software application that runs on the operating system, a web application is accessed by the web browser. The architecture of a web application is the client-server model. A mobile application is software that runs on mobile devices, such as Google Android OS for Android devices or Apple's iOS on iPhone devices. Like the web application, the frontend client is the software that runs on mobile devices. The backend also facilitates off-site data communication and persistence. The frontend client is restricted to the programming language on the device, such as Java or Kotlin for Android devices or Swift for Apple iOS devices (Tang, Thuan).

Mobile phones have several advantages over less mobile (or fixed location) devices such as touch screens. Mobile phones:

- Are owned by more people;
- Provide delivery in an instant, more convenient way;
- Can deliver personalized information to individual owners;

- Are cheaper to deploy;
- Provide other functions such as voice communication (Qiang et al, 2012).

Globally, there are three types of mobile application that any user can encounter:

a. Native mobile application:

These relate to software designed exclusively for a certain mobile platform.

b. Mobile web application:

They are associated with websites that are specifically designed for mobile optimization. The Internet browser on a mobile device is used to access these websites.

c. Hybrid mobile application:

These latter are regarded as a hybrid of native apps and web apps. They are, in fact, compatible with all mobile platforms (Chong et al, 2014).

3.3 Importance

Agricultural apps have significant potential to modernize the agricultural sector in both developed and developing countries. For example, they can help small-scale producers increase their income, reduce transaction costs in supplying and distributing products, improve traceability and quality criteria for consumers, and create new opportunities for financial institutions. (Qiang, Christine Zhenwei and Kuek, Siou Chew and Dymond, Andrew and Esselaar, Steve)

The respondents reported to have used their mobile phones for the following agriculture related activities: ordering animal feeds, getting market prices for the farm produce, making mobile payments to workers and agro-veterinary dealers, inquiries on veterinary services, getting information on animal breeds, getting information on the gestation of a cow, looking for available farm workers, getting information on farm machinery, finding market for the farm produce and getting advice from various source (Gichamba & Lukandu, 2012).

3.4 Examples of agricultural apps

There are a lot of more mobile apps aiding farmers in their venture (Table 1). Some of these apps work for a global audience. Others are designed for local use, depending on location. Regardless, they help solve age-old problems in agriculture and make tasks easier. They have become an integral part of agritech.

However, this is hardly the limit. As they look ahead, the future of agritech promises even more groundbreaking innovations. These innovations would be driven by advancements in artificial intelligence, the Internet of Things (IoT), and blockchain technology. It's expected that mobile apps will keep evolving. Integration with emerging technologies will further push the boundaries in productivity, and sustainability. And they hold the potential to address global food security challenges (Costopoulou et al, 2016).

Table 1. Agricultural Mobile Apps (Costopoulou et al, 2016)

Category	Android	iOS
Business and financial data	121	123
Animal production	65	65
Farm management-Crops	69	91
Pests and diseases	20	24
Agricultural technology and innovation	73	88
Agricultural machinery	39	35
Spraying related activities	30	31
Weather forecast	18	17
Training	41	39
Agricultural news	41	46
Other	44	30

Table 1 displays the actual number of Android and iOS mobile apps for each category. Because the Windows Phone Store is very new, it only provides **42 mobile agricultural applications**. Many of them are available in more than one app store.

3.4.1 Farmable

Farmable is a comprehensive farm management mobile app designed to streamline agricultural operations and optimize productivity for farmers of all scales. It is like a digital hub for farm management, as it pools together resources and tools matching farmers' everyday activities.

Additionally, the app has a user-friendly interface and intuitive functionalities that empower farmers to take control of their operations in a centralised platform.

Farmable's key features include:

- Task Scheduling:

Farmable allows users to schedule tasks such as planting, irrigation, fertilisation, and pest control with precision and efficiency. With such a degree of control, farmers can schedule and prioritise tasks for timely execution. This leads to increased productivity and reduced downtime.

- Crop Planning:

Based on factors like soil health, climatic conditions, and market demand, farmers can plan their crop rotations. Farmable allows them to plan their cropping system, select the most suitable variety, and

- Optimize planting:

This allows farmers to maximize yield, minimize risk, and optimize resource allocation. It also gives farmers the chance to keep historical data for future reference and informed decision-making.

- Inventory Management

Farmable allows farmers to track and manage their resources. They can manage their inventory of seeds, fertilizers, pesticides, and other inputs. This is a massive upgrade to traditional record-keeping and management systems. It ensures adequate supply levels and prevents stockouts.

- Field Monitoring

Farmable enables farmers to monitor field conditions, crop growth stages, and pest/disease outbreaks through real-time data visualisation and analytics. With this, they can detect issues early and implement timely interventions. As a result, crop loss is minimised and investment is preserved (Imonikhe, 2024)

2.4.2 Locus Map

Locus Map serves as a digital navigator for farmers. It offers them access to detailed maps, GPS tracking, and route planning tools to navigate their fields with ease. Typically, the app was designed to enhance operational efficiency and offer precision in navigation. Some of the app's exciting features include:

- Detailed Maps

Locus Map offers access to detailed maps with customizable layers, including satellite imagery, topographic data, and field boundaries. With the app, farmers can accurately map out their fields, identify land features, and visualize terrain variations. As a result, they can plan and execute their activities with greater precision.

- GPS Tracking:

The app provides real-time GPS tracking that allows farmers to monitor their movements. Additionally, they can track field operations, and navigate to specific locations within their fields. In operations like soil sample collection, the GPS feature allows farmers to collect samples precisely from different locations in the farm. With the coordinates of these sample points, farmers can draft nutrient distribution maps across their farms.

- Field Boundary Mapping

Farmers can use Locus Map to accurately map out field boundaries, delineate land parcels, and establish virtual boundaries for precision farming practices. With well-defined virtual boundaries across their fields, farmers can optimise planting patterns. And as a trend in smart irrigation, GPS can also help manage irrigation zones and implement precision farming techniques.

- Offline Access

Locus Map offers offline access to maps and navigation functionalities. So, in areas with limited or no internet connectivity, farmers can navigate their fields seamlessly. They can record data, and execute field operations without interruption (Imonikhe, 2024)

3.4.3 Agrivi

Agrivi is designed to address various complexities of modern agriculture. It's more like a digital hub that empowers farmers with control over several aspects of their operations. They can track crop performance and analyse financial metrics, monitor field conditions and streamline their workflow, increase yield, and enhance profitability.

Key features include:

- Crop Planning

Agrivi offers tools for crop planning and management, allowing farmers to create tailored crop plans, schedule tasks, and optimize input usage. Through strategic crop plans, farmers can make the most out of resource allocation for improved profitability.

- Field Monitoring

The platform enables farmers to monitor field conditions, track crop growth stages, and assess plant health through real-time data visualization and analytics. With this info, farmers can detect issues early, implement timely interventions, and minimize crop losses.

- Financial Tracking

With this feature, financial analysis and tracking are possible. Farmers can monitor expenses, revenues, and profitability metrics in real time. They can identify areas for improvement, make informed budgeting decisions, and ultimately increase their bottom line.

- Data Integration and Insights

The platform integrates data from various sources to help in decision-making. For example, data from weather stations and satellite imagery are collected to offer predictive analytics and forecasting. This is important to anticipate challenges, minimize risks, and make informed decisions. As a result, farmers enjoy sustainable and more resilient farming practices (Imonikhe, 2024)

3.4.4 AgriWebb

Agriwebb is a leading livestock management app in livestock technology. It offers tools for herd recording, mustering, health monitoring, and financial tracking. It offers a wide range of functionalities like individual animal data recording, health and performance metrics tracking, and operations optimization. Agriwebb empowers farmers to make data-driven decisions and optimize their operations for improved herd health and productivity.

Some of its major features include:

- Herd Recording

Agriwebb enables farmers to record and track detailed information about individual animals, including birth dates, weights, treatments, and movements. With these records, they can track the performance and health of individual animals, identify trends, and make informed breeding and management decisions.

- Mustering and Movement Tracking

The app offers tools for planning and executing mustering activities. It can also track animal movements, and manage grazing rotations. This enables farmers to optimise grazing patterns, minimise stress on animals, and maximise pasture utilisation.

- Health Monitoring and Treatment Records

Agriwebb allows farmers to monitor animal health status, record treatments, and vaccinations, and track disease outbreaks with ease. This helps to reduce disease spread, and address health complications early,

- Cloud-Based Data Storage and Accessibility

Agriwebb offers cloud-based data storage. So, farmers can access and manage their records from anywhere, anytime, and from any device. They can stay connected with their data even when they are on the field. This fosters collaboration between workers and management to improve operational efficiency (Imonikhe, 2024)

3.4.5 Farmbrite

Farmbrite is an all-in-one online farm and ranch management software designed to help farmers manage their day-to-day operations from one central location. It provides tools for measuring farm profits, tracking expenses, monitoring crop production, keeping detailed animal records, and much more. The software aims to simplify the entire farm management process by offering integrated record-keeping, planning, management, tracking, sales, and reporting software that enables modern farmers and ranchers to run a thriving agriculture business.

Farmbrite is suitable for all types and sizes of farms and livestock producers who are looking to improve work orders while effectively tracking all their data in one secure location. Native mobile apps allow on-the-go access making it easy for users with iOS or Android devices to keep tabs on their operation anytime from anywhere. Additionally, Farmbrite simplifies crop planning procedures by automating yield output estimates for crops & livestocks which makes seed ordering easier as well. By streamlining inventory tracking along with customer records & fulfillment through its integrated e-commerce portal; farm owners can easily market & sell products online without having to move offline. Overall Farmbrite helps organize farming activities while providing useful insights for better decision-making such as setting goals & improving yields (Anonyme, 2024).

2.4.6 Plantix

Plantix is prominently known for its AI-powered image recognition technology. The technology diagnoses plant diseases, nutrient deficiency, and pest infiltration. Think of it as a virtual crop doctor which allows for quick, precise, and accurate diagnosis of crop health. Farmers can just take a photo of their plants, and Plantix gives them instant diagnosis and recommendations.

However, plantix offers more than just disease and pest identification. It comes with other exciting features, such as fertilizer calculation, cultivation tips, and resources. And if users have any questions, Plantix allows them access to a community, where they can share knowledge.

Plantix has several exciting features, which include:

- Image Recognition

Plantix uses advanced image recognition technology to analyze photos of plants and identify symptoms of diseases, pests, and nutrient deficiencies. It saves farmers time and effort, enabling them to identify issues early and take proactive measures to protect their crops.

- Crop Library

The app features a comprehensive crop library with information on a wide range of crops, including common diseases, pests, and nutrient requirements. Farmers can access valuable information on crop management practices and disease prevention strategies. Additionally, they can learn nutrient management techniques, enabling them to make informed decisions and optimize crop health.

- Community Support

Plantix fosters a vibrant community of farmers, agronomists, and experts who share knowledge, insights, and best practices for crop health management. They can tap into the collective wisdom of the Plantix community, seeking advice, troubleshooting problems, and learning from the experiences of others to improve their crop management practices (Imonikhe, 2024)

2.5 Conclusion

The integration of web applications in the agricultural sector is profoundly transforming farming practices by providing farmers with real-time access to crucial information and innovative tools. These web platforms optimize farm management by delivering precise data on weather forecasts, soil conditions, pest identification, and crop health monitoring. With web applications, farmers can make informed decisions, improve productivity, and adopt sustainable practices. Moreover, these platforms facilitate connections between farmers, markets, resources, and expert advice, creating a more informed and interconnected agricultural community. In summary, web applications play a vital role in enhancing agricultural efficiency, ensuring food security, and promoting sustainable environmental management.

Chapter 4: Materials and methods

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4.1 Introduction

The rise of convolutional neural networks (CNNs) has revolutionized the field of computer vision, particularly in agricultural applications. Detecting and classifying apple diseases is a crucial issue for apple growers, as it has a direct impact on crop productivity and quality. Apple diseases such as scab, rust and fire blight can cause significant economic losses, and require early identification for effective management. In this context, the application of CNNs offers a promising solution for automating and improving the accuracy of disease detection.

In this chapter, we will describe our model for the detection and classification of apple diseases. The proposed solution is based on convolutional architecture. The latter is divided into several key stages: data collection, image pre-processing, model construction and finally model training and performance evaluation.

4.2 Data collection

The first stage, data collection, is the most important step in designing an effective model. To build a robust Deep Learning model, it is essential to have a rich and varied dataset, including images representing different apple tree diseases under various angles and lighting conditions. Potential data sources include public databases and contributions from the scientific community. Annotation and filtering are also crucial to ensure the quality of the data used for model training.

As part of this project to detect and classify apple diseases, collecting adequate data is a crucial step. To this end, we used datasets available on Kaggle (Biswal) (Kumar, 2022) (SANKALANA) (Nahida Bashir, 2022) (Heroseo, 2020), a platform renowned for hosting varied, high-quality datasets.

The data required for this project comes from several datasets available on Kaggle, specifically focused on apple diseases. These datasets contain thousands of images of apple leaves, covering many conditions and disease types. In particular, the classes of interest for our project are:

- Apple Scab
- Black rot
- Rust

- Disease-free class (Healthy) (Figure 14).

These classes were chosen for their prevalence and importance in apple disease management. Apple scab and black rot are among the most common and damaging diseases affecting apple trees, while the disease-free class serves as a benchmark for assessing tree health.

Figure 14. a. Apple Black-rot; b. Apple Scab; c. Apple Rust; d. Disease-free class (Healthy).

4.3 Data structure

The Kaggle datasets are well structured, making them easy to use for training CNN models. Each image is accompanied by metadata specifying the class to which it belongs. Images of apple leaves, captured under different angles and lighting conditions, are saved in JPEG format.

Figure 15. Screenshot of datasets used

Each image is labeled with its corresponding class (scab, rust, black rot, or healthy). This annotation is essential for supervised training of the CNN model.

4.4 Data preparation

Before using these data to train the model, a number of preparations are necessary to guarantee their quality and relevance. Images are downloaded from Kaggle and organized into separate directories according to their respective classes. This organization facilitates the data loading and pre-processing process during model training. A data cleaning process is undertaken to eliminate poor quality or mislabeled images. This includes the removal of blurred, underexposed or overexposed images, as well as duplicates.

To avoid class imbalance that could bias the model, balancing techniques are applied. These may include under-sampling majority classes or over-sampling minority classes.

4.5 Image pre-processing

Image pre-processing is a crucial step in preparing the data for ingestion by the CNN model. The following pre-processing techniques are applied:

- **Resizing:** All images are resized to a uniform size **(e.g. 224x224 pixels)** to ensure compatibility with the chosen CNN architecture.
- **Normalization:** Image pixel values are normalized to standardize the range of input values, helping to speed up model convergence during training.
- **Data augmentation:** To enrich the dataset and improve model robustness, data augmentation techniques are used. These include transformations such as rotation, flipping, cropping and brightness adjustments. These augmentations enable us to simulate the diversity of real conditions encountered in the field.

Careful data collection and preparation is the first step towards building an effective CNN model for apple disease detection and classification. By using rich and diverse data from Kaggle, and applying rigorous pre-processing techniques, we lay the solid foundations needed to train a powerful and reliable model. These steps ensure that the model has the information it needs to learn and generalize effectively, facilitating early and accurate detection of apple diseases, with significant implications for crop management and the reduction of agricultural losses.

4.6 Model construction

This section details the design and implementation process of the CNN model used in this project. The architecture of the CNN model is carefully designed to maximize disease detection accuracy while maintaining reasonable complexity for efficient training. The model comprises several convolutions, normalization, pooling and fully connected (dense) layers.

4.7 Architecture details

The CNN model is implemented using the PyTorch framework, enabling greater flexibility and efficiency in building and training the network. The detailed architecture is as follows:

1. **Convolution Layer 1 (Conv1):**
   - **Input size:** 3×224×2243×224×224 (RGB color channels)
   - **Operations:** Convolution with 32 filters of size 3×33×3, padding = 1.
   - **Output size:** 32×224×22432×224×224
   - **Usefulness:** Extract basic features such as edges and textures.
2. **Activation (ReLU):**
   - **Utility:** Introduce non-linearity, enabling the network to learn more complex functions.
3. **Batch Normalization:**
   - **Usefulness:** Introduce non-linearity, enabling the network to learn more complex functions.
4. **Convolution Layer 2 (Conv2):**
   - **Input size:** 32×224×22432×224×224
   - **Operations:** Convolution with 32 filters of size 3×33×3, padding = 1.
   - **Output size:** 32×224×22432×224×224
   - **Usefulness:** Refine previously extracted features.
5. **Activation (ReLU)**
6. **Batch Normalization**
7. **Max Pooling (MaxPool1):**
   - **Operations:** Pooling with window size 2×22×2, stride = 2.
   - **Output size:** 32×112×11232×112×112
   - **Usefulness:** Reduce dimensionality while retaining essential information.

8. **Convolution Layer 3 (Conv3):**
   - **Input size:** 32×112×11232×112×112
   - **Operations:** Convolution with 64 filters of size 3×33×3, padding = 1.
   - **Output size:** 64×112×11264×112×112
   - **Usefulness:** Extract more complex features.
9. **Activation (ReLU)**
10. **Batch Normalization**
11. **Convolution Layer 4 (Conv4):**
    - **Input size:** 64×112×11264×112×112
    - **Operations:** Convolution with 64 filters of size 3×33×3, padding = 1.
    - **Output size:** 64×112×11264×112×112
    - **Usefulness:** Refine more complex features.
12. **Activation (ReLU)**
13. **Batch Normalization**
14. **Max Pooling (MaxPool2):**
    - **Operations:** Pooling with window size 2×22×2, stride = 2.
    - **Output size:** 64×56×5664×56×56
    - **Usefulness:** Further reduce dimensionality while retaining important features.
15. **Convolution Layer 5 (Conv5):**
    - **Input size:** 64×56×5664×56×56
    - **Operations:** Convolution with 128 filters of size 3×33×3, padding = 1.
    - **Output size:** 128×56×56128×56×56
    - **Usefulness:** Capture even more complex and abstract features.
16. **Activation (ReLU)**
17. **Batch Normalization**
18. **Convolution Layer 6 (Conv6):**
    - **Input size:** 128×56×56128×56×56
    - **Operations:** Convolution with 128 filters of size 3×33×3, padding = 1.
    - **Output size:** 128×56×56128×56×56
    - **Usefulness:** Further refinement of complex features.
19. **Activation (ReLU)**
20. **Batch Normalization**
21. **Max Pooling (MaxPool3):**

- **Operations:** Pooling with window size 2×22×2, stride = 2.
- **Output size:** 128×28×28128×28×28
- **Usefulness:** Further reduce dimensionality and prepare features for deeper layers.

22. **Convolution Layer 7 (Conv7):**
    - **Input size:** 128×28×28128×28×28
    - **Operations:** Convolution with 256 filters of size 3×33×3, padding = 1.
    - **Output size:** 256×28×28256×28×28
    - **Usefulness:** Capture even finer, more detailed features.
23. **Activation (ReLU)**
24. **Batch Normalization**
25. **Convolution Layer 8 (Conv8):**
    - **Input size:** 256×28×28256×28×28
    - **Operations:** Convolution with 256 filters of size 3×33×3, padding = 1.
    - **Output size:** 256×28×28256×28×28
    - **Usefulness:** Refine highly detailed features.
26. **Activation (ReLU)**
27. **Batch Normalization**
28. **Max Pooling (MaxPool4):**
    - **Operations:** Pooling with window size 2×22×2, stride = 2.
    - **Output size:** 256×14×14256×14×14
    - **Usefulness:** Reduce final dimensionality before entering fully connected layers.

Fully Connected Layers

1. **Flatten Layer:**
    - **Operations:** Flatten the three-dimensional output of the convolution layers into a one-dimensional vector.
    - **Output size:** 256×14×14=50176256×14×14=50176
    - **Usefulness:** Prepares data for fully connected layers.
2. **Dense Layer 1:**
    - **Input size:** 5017650176
    - **Operations:** Dense layer with 1024 neurons.
    - **Output size:** 10241024
    - **Usefulness:** Perform linear combination of extracted features.

3. **Activation (ReLU)**
4. **Dropout:**
   - **Dropout rate:** 0.4
   - **Usefulness:** Reduce overlearning by randomly deactivating neurons during training.
5. **Dense Layer 2:**
   - **Input size:** 10241024
   - **Operations:** Dense layer with a number of neurons equal to the number of KK classes (here 3 classes).
   - **Output size:**KK
   - **Usefulness:** Generate scores for each class.

Output Layer

- **Output size:** 33 (corresponding to classes: apple scab, black rot, disease-free)
- **Usefulness:** To provide probabilities for each disease class, enabling final classification of the input image.

This detailed architecture enables the model to efficiently capture and extract relevant features at different levels of complexity, while reducing dimensionality and avoiding overlearning, thus guaranteeing optimal performance for apple disease detection and classification.

Chapter five: Results

Chapter 5: Results

5.1 Introduction

In this section, we present the results of our apple leaf disease detection application. The performance of the model was evaluated using several metrics, including accuracy, precision, recall. Additionally, we conducted a comparative analysis with existing models and performed real-world testing to validate our application.

ALGAGRIVISION is a sophisticated web application developed for the identification and classification of diseases affecting apple trees through the scanning of symptoms present on their leaves. Utilizing advanced imaging technology, the application conducts a meticulous analysis of leaf symptoms to detect any anomalies or potential diseases. In addition to its diagnostic capabilities, **ALGAGRIVISION** provides comprehensive recommendations for both biological and chemical control measures. The application suggests suitable homologated phytosanitary products, enabling farmers to implement effective strategies for disease management. By integrating agronomic expertise with state-of-the-art technology, **ALGAGRIVISION** aims to enhance crop yield and quality, minimize crop loss, and strengthen consumer confidence through precise and reliable disease diagnostics.

5.2 Interface

The interface of **ALGAGRIVISION** web application is designed to provide users with an intuitive and efficient experience, facilitating the identification and management of apple tree diseases. The primary components of the interface include the following Taskbar:

Home (Figure 16)

The Home section serves as the central hub for the application, offering users a comprehensive overview of its functionalities and providing quick access to the main features. This section includes an introduction to the application's capabilities and guides users on how to utilize the various tools available.

The home page also provides easy navigation to other parts of the site.

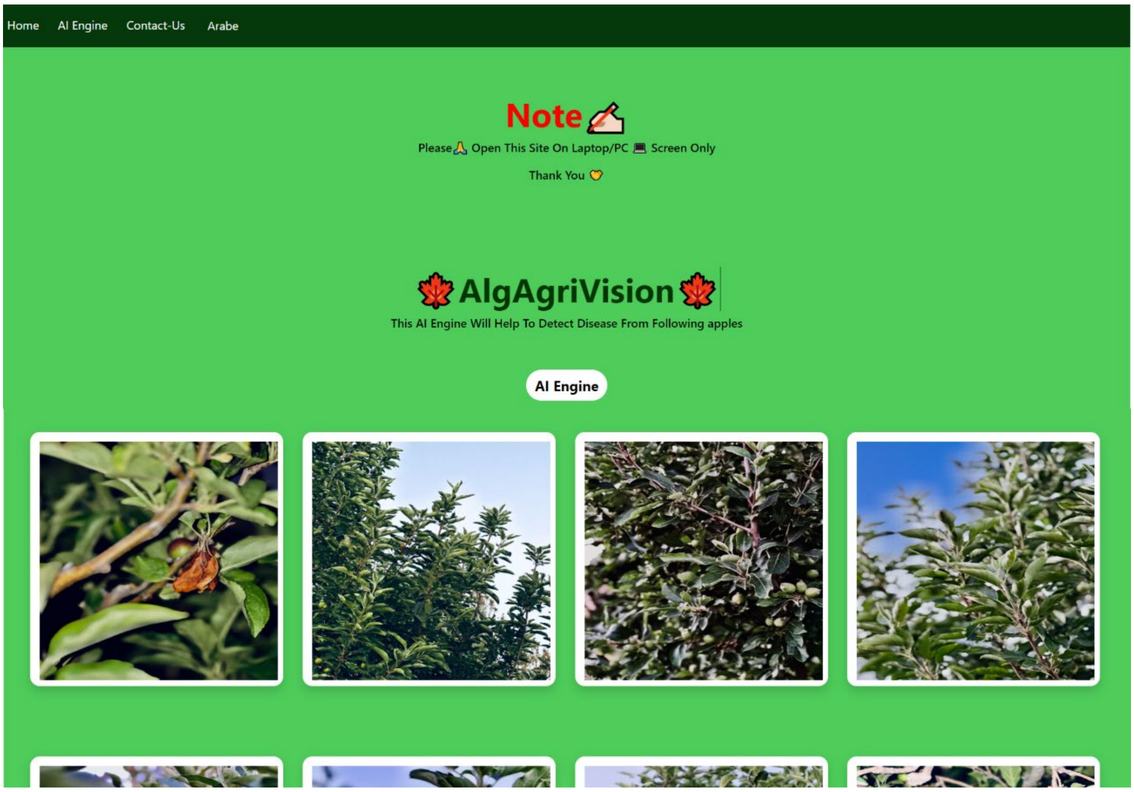

Figure 16. Home page

Multilingual Interface (Figure 17)

The Language section allows users to select their preferred language for the application interface.

The Apple Leaf Disease Detection App, available in three languages (**Arabic, French, and English**) is a revolutionary tool designed to assist apple growers in Algeria in maintaining the health of their orchards. This multilingual capability ensures that the app is accessible to a diverse range of users, making it a versatile and inclusive solution for apple leaf disease management.

- Language Selection: Users can easily switch between **Arabic, French, and English**, ensuring the app is accessible to speakers of these languages.

- Localized Content: All app content, including disease information, treatment recommendations, and user support, is available in the selected language, providing a seamless experience for users.

Figure 17. Choosing language

AI Engine (Figure 18)

The AI Engine section is the core feature of **ALGAGRIVISION**, enabling users to upload images of apple tree leaves for disease analysis. This section leverages advanced artificial intelligence algorithms to accurately identify and classify diseases based on the uploaded images. Detailed results and recommended actions are displayed upon completion of the analysis.

Figure 18. AI Engine Function

Contact Us

The Contact Us section provides users with the means to reach out to the support team for any assistance or inquiries. This section includes a contact form, email address, and other relevant contact information to ensure users can easily seek help and receive timely responses to their queries.

Each component of the taskbar is strategically designed to enhance user experience, streamline navigation, and ensure that all essential functionalities are easily accessible. The professional and user-friendly design of the interface reflects **ALGAGRIVISION**'s commitment to providing a reliable and effective tool for managing apple tree health.

5.3 Steps for Using the AI Engine Functionality:

5.3.1 Selecting the Image: Upon reaching the AI Engine interface, users are prompted to choose an image of an apple tree leaf to be scanned. They can do so by clicking on the "Choose Image" button and selecting the appropriate image from their device.

Clicking on the "Submit" Button: After selecting the image, users are required to click on the "Submit" button to initiate the scanning process. The application immediately uploads the image and sends it to the analysis servers.

5.3.2 Scanning and Analysis Process:

Image Upload: The application uploads the selected image from the user's device to the central server for analysis.

Image Analysis: The AI engine employs advanced algorithms to analyze the uploaded image. The image is thoroughly examined to identify any symptoms of potential diseases on the apple tree leaves.

5.3.3 Displaying Results (Figures 19-21)**:**

Upon the conclusion of the analysis, users are presented with the results. The diagnostic report provides comprehensive details regarding the identified disease type, accompanied by recommendations for appropriate biological and chemical treatments in **Arabic, English,** and **French.** This multilingual approach ensures accessibility and clarity for users across different linguistic backgrounds, enhancing their understanding and facilitating informed decision-making in managing apple tree health.

Figure 19. Displaying Results in Arabic

Figure 20. Displaying Results in French

Each part aims to comprehensively address the management of the disease, covering its description, preventive measures, and chemical treatment options.

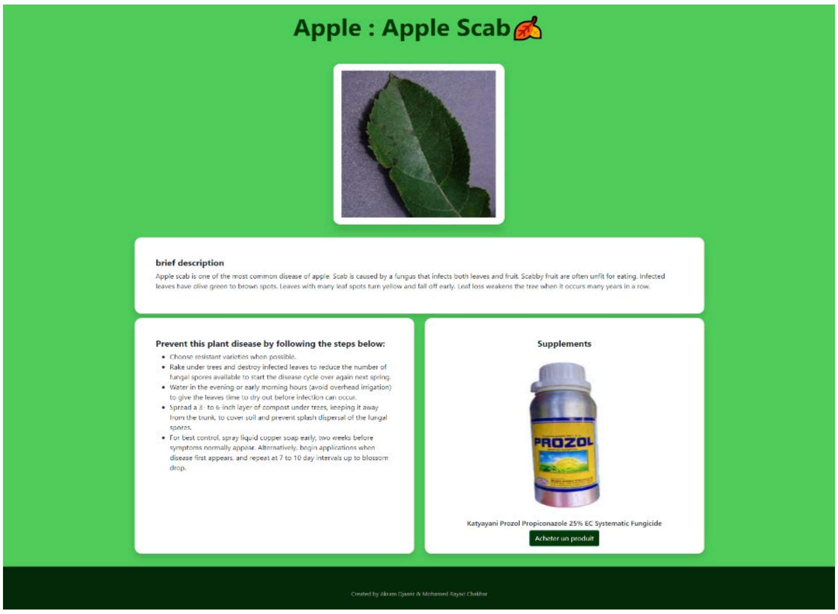

Figure 21. Displaying Results in English

Results page, when displayed in brief form, offers a user-friendly and accessible interface tailored for users.

The results section is structured into three distinct parts :

- **Disease Description :** This section provides a detailed description of an apple disease.
- **Disease Prevention Steps :** Here, various preventive measures are presented, including cultural practices and environmental management methods.
- **Chemical Control :** This part discusses chemical control strategies, highlighting a specific registered pesticide product for combating the disease.

Health confirmation (Figure 22):

- **Healthy Leaf Verification:** When an image of a healthy leaf is uploaded, the app confirms its health status, providing peace of mind to the grower.
- **Health Tips:** The app offers tips on how to maintain the health of the leaves and prevent future diseases, and suggests effective fertilizer to increase yield.

Figure 22. Disease-free class (Healthy)

Displays the uploaded images with notes confirming the absence of any disease symptoms.

5.4 App’s features

Here's a detailed description of the app's features and functionalities:

Cure Methods: The app offers a variety of treatment options, including organic and natural remedies, mechanical treatments, and cultural practices that can help manage and cure the disease.

Chemical Products: For more severe cases, the app recommends specific chemical products **approved in Algeria**, including fungicides and bactericides, that are effective against the identified disease.

ALGAGRIVISION App, the first of its kind in our country, represents a significant advancement in agricultural technology and precision farming. This innovative app is tailored specifically for apple growers, offering a comprehensive solution for maintaining the health of apple orchards through early detection and precise diagnosis of leaf diseases.

General Conclusion

General Conclusion

In conclusion, the advancement of artificial intelligence applied to apple leaf disease detection, embodied by **ALGAGRIVISION**, represents a crucial step towards more innovative and sustainable agriculture. This intelligent system not only accurately identifies and classifies apple leaf diseases, but also offers recommendations for appropriate biological and chemical interventions, considering the phytosanitary products registered in Algeria.

The planned extension to cover all apple diseases reflects our commitment to providing growers with comprehensive tools for proactively managing the health of their crops. By facilitating collaboration between contributors in the agricultural sector, ALGAGRIVISION aims to strengthen farming practices and improve farm resilience in the face of climatic and health challenges.

Our vision also includes setting up an early warning system, enabling farmers to act quickly against emerging diseases. By supporting farmers' ongoing training in crop protection practices, we aim to optimize their ability to preserve the productivity and sustainability of apple orchards.

In short, **ALGAGRIVISION** embodies the promising future of digital agriculture, where technology and innovation combine to meet current and future agricultural needs. By integrating these advances, we are convinced that we can make a significant contribution to the efficiency and sustainability of agriculture, while opening up new prospects for an even more effective use of artificial intelligence in agriculture.

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