Deep Learning-Based Detection of Diseases in Strawberry Plants

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Abstract: Strawberry cultivation is highly susceptible to various diseases, significantly impacting yield and quality. Early and accurate detection of plant diseases is crucial for effective management and mitigation strategies. Traditional disease detection methods, such as visual inspection and laboratory testing, are time-consuming and often inaccurate. This study uses image-based analysis to explore the application of deep learning techniques for the automated detection of diseases in strawberry plants. We employed transfer learning on pre-trained convolutional neural network (CNN) models, including Xception, DenseNet169, and MobileNet, to classify and predict plant diseases. The models were trained and evaluated using a diseased and healthy strawberry plant images dataset. Furthermore, an ensemble model was developed to enhance prediction accuracy by combining multiple deep-learning models. A web-based application was designed using Flask, HTML, CSS, JavaScript, and Bootstrap, enabling farmers to upload plant images and receive real-time disease diagnosis and treatment recommendations. Experimental results indicate that deep learning models offer high accuracy in disease detection, thereby providing an efficient and scalable solution for disease management. This research demonstrates the potential of AI-driven approaches in precision agriculture, contributing to improved crop health, yield, and sustainable farming practices.

1. Introduction

Crop diseases are an ongoing threat to agriculture since they can significantly reduce crop yields and global food production. Crop diseases, such as bacterial, viral, and fungal infections, concern farmers worldwide [14]. However, the industry uses several tactics to address these problems efficiently. Strawberry cultivation is an important agricultural sector that faces various problems, including disease conditions that can result in severe crop yield and quality losses. Farmers must identify and manage such diseases to safeguard crops, prevent losses, and sustain food security. In the following paragraphs, we will look at how the agriculture business, namely strawberry farming, deals with plant diseases and how they diagnose and manage them [3]. Strawberries are a popular fruit that is enjoyed by people all around the world. They are delicious and nutritious, with high vitamin C, fibre, and antioxidants. There are many different varieties of strawberries, each with a unique flavour and texture. Strawberry diseases can cause significant damage to plants and reduce fruit production. Awareness of their symptoms and

causes is essential to prevent and manage these diseases. Proper plant care, such as maintaining proper air circulation, avoiding overcrowding, and using clean water for irrigation, can help prevent the spread of disease.

Additionally, fungicides and other control measures can effectively manage strawberry diseases [6]. With proper care and attention, strawberry plants can produce healthy, delicious fruit for years. Unfortunately, like all plants, strawberries are vulnerable to disease. Several diseases can affect strawberries, including powdery mildew leaf, grey mould, leaf spot, angular leaf spot, and blossom blight. These diseases can cause significant damage to strawberry plants and reduce crop yields, making it essential to be aware of their symptoms and how to prevent and manage them [4].

Farmers diagnose these diseases in various ways, including visual examinations, diagnostic equipment, and laboratory analysis. Visual inspections involve looking for indications of problems like leaf pigmentation, becoming wilted, or discoloration on the plants. Plant pathogen detection labs, disease guidebooks, and digital image evaluation can assist farmers in precisely identifying the disease [7]. Plant samples are collected and sent to a diagnostic facility for laboratory analysis. The laboratory study can identify the organism that causes the disease and its fatigue, which is necessary for determining the most viable treatment options. Early diagnosis of diseases in plants can be vital for limiting disease transmission, decreasing losses, and enhancing management strategy success [9]. Farmers can control the disease's spread through numerous kinds of management strategies once it has been recognized [10]. Techniques for controlling chemicals, biological processes, and culture are among these methods. Fungicides and various substances are used in chemical control to combat the disease that causes it [5]. However, using chemicals can be expensive and have unfavourable environmental impacts. As a result, farmers should strive to utilize fewer chemicals whenever possible and incorporate other management techniques with chemical control.

Utilizing the diseases' natural enemies to regulate the diseases is known as biological control. Using helpful insects or microorganisms that fight the infection or fight with it for resources is one way to do this. Cultural control strategies encompass modifying the growing environment to lower disease compulsion. This may include crop rotation, hygienic measures, and enhancing soil health. Deep learning has revolutionized the agricultural industry by helping farmers accurately predict and identify plant diseases. Deep learning in agriculture has considerably improved disease diagnosis, allowed farmers to act quickly to combat diseases, and decreased the adverse impacts on crop quality and productivity [7]. This essay will go through the advantages of deep learning and how it has aided the agriculture industry in predicting plant diseases. The usual method of finding plant diseases entails eye examinations, laboratory analysis, and specialized training. This method can take an extended period and frequently results in a delayed response, which causes severe crop losses. Deep learning algorithms, on the other hand, provide a highly effective and precise alternative strategy for disease identification.

To identify disease symptoms, these algorithms are trained on enormous databases of plant images, including both healthy and diseased plants. Once instructed, the algorithms accurately classify newly acquired images as healthy or ill. Through early disease detection and rapid response, farmers can significantly reduce crop losses. Deep learning in agriculture has a wide range of advantages. The first advantage is that it enhances disease detection, allowing farmers to recognize diseases quickly and take measures to avoid them, reducing the negative impact on crop productivity and quality [12]. Moreover, deep learning algorithms are incredibly effective and can quickly examine many plant images, reducing the time and cost involved in disease identification. Thirdly, by decreasing the need for chemical-based pesticides through early disease identification, applying deep learning algorithms improves sustainable agricultural practices. Finally, early disease diagnosis can boost crop yields, enhancing food security and farmers' general financial well-being. Several deep-learning applications have been developed in the agricultural sector in recent years. For example, Plant Village is an application for mobile devices that analyses images provided by farmers to identify plant diseases.

The app's database of nearly 100,000 images enables it to recognize disease symptoms and offer treatment recommendations [11]. Phyto Oracle is another deep learning-based technology that uses plant images to predict crop yields. The technology analyses plant images and calculates agricultural yield using a neural network, enabling farmers to manage their crops based on data. A machine learning-based application called Deep Leaf uses photos of leaves to identify nutrient deficits in plants. The device helps farmers to detect nitrogen, phosphate, and potassium deficits and modify their fertilizer application as required [16]. Since deep learning has improved disease detection and made it possible for farmers to act quickly, diseases have less impact on crop yield and quality. Increased productivity, decreased usage of pesticides, deeper disease detection, and higher crop yields are all advantages of deep learning in agriculture [7]. Plant Village, Phyto Oracle, and Deep Leaf are just a few deep learning-based applications developed to assist farmers with disease detection and control. Deep learning is expected to grow progressively important for agriculture as it continues to develop, assisting growers in improving crop yields, lowering losses, and preserving food security [13].

Ensemble models are helpful in the identification of strawberry diseases because they integrate the results of different models to provide a substantially more accurate and reliable predicting tool. One of the key benefits of ensemble models is the ability to overcome the limitations of individual models. An ensemble model, which integrates the predictions of various models and

learns to balance each approach's positive and negative aspects, is likely to produce the most accurate prediction [8]. This can be particularly helpful in identifying complex diseases where no single model or feature can provide a reliable classification.

Ensemble models can help in the early diagnosis of strawberry diseases by integrating several elements or factors, such as texture, colour, and form, that can be extracted from plant images or sensor data [15]. The ensemble approach has the potential to efficiently integrate all these variables, maximizing each feature's ability to forecast and produce an accurate diagnosis. An ensemble technique is a helpful tool for diagnosing strawberry diseases by combining the predictions of various models and characteristics to generate a more accurate and trustworthy predictive model [1]. With the help of this technique, farmers can act quickly to prevent crop losses and ensure the quality of their harvest. By integrating the predictions of various models to create a more precise and reliable predictive model, ensemble models may help detect strawberry diseases. The capacity of ensemble models to overcome the limitations of individual models is one of its main benefits. An ensemble model can develop the ability to assess each model's advantages and disadvantages and provide a more accurate prediction by combining the results of numerous models. This can be especially helpful when diagnosing complicated diseases without a sufficient model or feature. To maximize each feature's predictive power and produce an accurate diagnosis, the ensemble model can learn how to integrate these features [2]. Overall, by combining the predictions of different models and attributes to produce a more precise and reliable predictive model, an ensemble model can be a useful tool for identifying strawberry diseases. By using this strategy, farmers may prevent crop losses and ensure the quality of their produce.

1.1. Types of Strawberry Diseases

1.1.1. Powdery Mildew Leaf

Strawberry plants are frequently afflicted by the fungal disease known as powdery mildew leaf. The plant's leaves, stems, and flowers appear as a powdery covering in shades of white or grey. This illness is more common in the late summer and early autumn because it flourishes in humid conditions (Figure 1).

Figure 1: Powdery mildew leaf

1.1.2. Gray Mold

Botrytis blight, commonly known as grey mould. Strawberries are susceptible to this fungus disease, which is more prevalent when it is rainy and muggy outside. The illness causes greyish-brown patches on the fruit, which later develop into a mouldy substance with a fuzzy grey texture. Fruit that has been infected becomes mushy, watery, and unsellable. Avoid crowding the plants, keep adequate air circulation, and remove affected fruit immediately to prevent grey mould (Figure 2).

Figure 2: Gray mold

1.1.3. Leaf Spot

Leaf spot is a bacterial disease that causes small, dark spots on strawberry plants' leaves. The disease can cause defoliation and reduce fruit production. It is spread through water and soil, so keeping the plants dry and using clean water for irrigation is essential. Copper-based fungicides can also be used to control leaf spots.

1.1.4. Angular Leafspot

Angular leaf spot is another bacterial disease that affects strawberries. It causes angular, water-soaked spots on the leaves, which later turn brown and dry. The infected leaves eventually drop from the plant, making the fruit deformed and unmarketable. The disease is spread through water and can be controlled using copper-based fungicides (Figure 3).

Figure 3: Angular leafspot

1.1.5. Blossom Blight

Blossom blight is a fungal disease that affects strawberry flowers. It causes the flowers to turn brown and die, reducing the plant's fruit production. Blossom blight thrives in wet and humid conditions and is spread through water. To prevent this disease, maintain proper air circulation, remove infected flowers promptly, and use fungicides if necessary (Figure 4).

Figure 4: Blossom blight

2. Literature Survey

We have developed this paper's strawberry plant disease prediction and classification application. This application is very helpful for the farmers. By using this application, farmers can upload images of diseased plants and get the prediction of the diseases of the main 5 strawberry plant diseases that we have implemented. After the user uploads the image, the disease description and cure methods are provided [1]. The web application has a simple UI with four primary pages: home, expert, pesticide, and contact us. The home page is the application's landing page and acts as a gateway to the application's abilities and capabilities [2]. On the main page, users may submit images of their strawberry plants, which the application will analyze using machine learning algorithms to discover and diagnose plant diseases. This feature allows users to acquire rapid and reliable disease detection without requiring specialized knowledge or equipment. Furthermore, the main page leads to the expert, pesticide, and contact us pages, allowing users to receive more extensive information or interact with the app's creators for help and criticism [3].

The expert page includes contact information for professionals in strawberry diseases, including researchers and botanists, to whom users can contact for more assistance. The contact information for the experts includes their names, affiliations, and

email addresses, allowing visitors to reach them directly for professional advice or help [5]. This feature guarantees that users receive access to the most up-to-date knowledge & expertise in the area, allowing them to make educated disease control and management decisions [6]. Finally, the expert page includes connections to the pesticide and contact us pages, allowing users to obtain more extensive information or contact the application's creators for assistance and comments [7]. The pesticide page contains advice for chemically controlling strawberry diseases that are both effective and safe. It includes a complete list of approved pesticides that may address different diseases and advice on applying them safely and efficiently. Users can look for pesticides depending on the ailment they want to treat or the active chemical they desire [4].

Users can contact the application's creators via the Contact Us page for technical help or comments. The website includes the application's email address, phone number, and physical location for users who wish to contact the team directly [8]. In this section, we are going to describe a brief description of the upcoming section in our strawberry disease detection and classification web application report [9]. The paper goes through the issue profile for the strawberry disease detection and classification web application in further detail. We outline the strawberry business's primary issues in disease diagnosis and control. This paper looks at the strawberry business's current disease detection and control system. We discuss the limits of traditional disease diagnostic methods, such as eye examination, and the possible economic and environmental consequences of crop losses and pesticide abuse [10].

3. Proposed Methodology

In a deep learning paper, the structure you've described typically outlines the organization of the paper's codebase or directory structure. Let's break down each component:
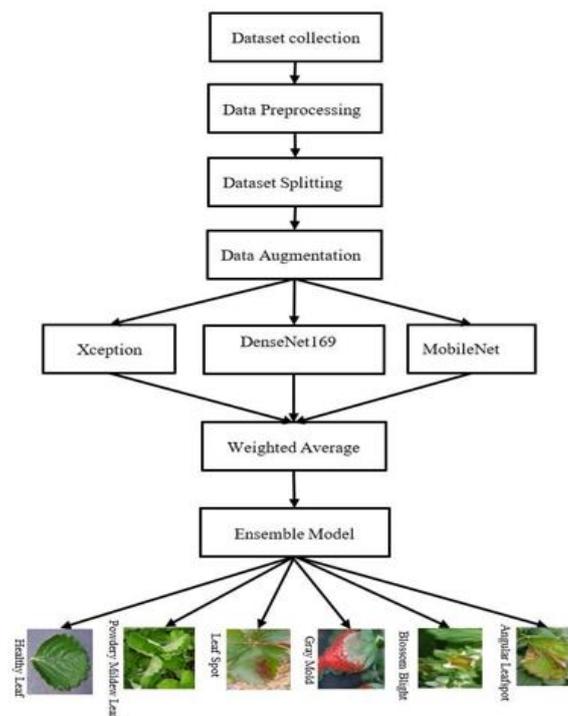

Figure 5: Flowchart for model training and design

3.1. Repository

This likely refers to the paper's root directory or main folder where all the paper files and subdirectories are stored. It may contain scripts, configuration files, documentation, and other resources related to the paper.

3.2. Preprocessing

This directory would contain scripts or modules responsible for data preprocessing tasks. Data preprocessing is crucial in deep learning papers to clean, transform, and prepare raw data before feeding it into the model for training. Preprocessing steps may include data normalization, resizing, augmentation, feature extraction, and data splitting (into training, validation, and test sets).

3.3. Classification

This directory is likely dedicated to implementing the paper's classification model(s). It would contain scripts, modules, or subdirectories related to building, training, evaluating, and deploying classification models using deep learning techniques. This could involve creating neural network architectures (e.g., convolutional neural networks for image classification), defining loss functions, configuring optimizers, and handling model training and evaluation processes.

3.4. Classes

This directory may contain class definitions or modules for defining custom classes or components used throughout the paper. A deep learning paper could include classes for defining the neural network architecture, custom layers, data loaders, loss functions, metrics, and other reusable components used across different paper parts. Overall, this directory structure provides a logical organization for a deep learning paper, separating different aspects of the paper (data preprocessing, model implementation, custom classes) into distinct directories for better code maintainability, readability, and reusability (Figure 5).

Pseudocode

```
Start
        Import necessary libraries. Load the pre-trained model.
        Define a function to predict the disease in each image.
          Load the image and preprocess it.
          Predict the disease using the loaded model.
          Return the predicted disease and the corresponding HTML page.
        Create a Flask instance.
        Define routes for different pages and HTTP methods.
          Render the corresponding HTML page for each route and HTTP method.
        Define a route to accept image uploads and predict the disease.
          Get the uploaded image.
          Predict the disease using the pred_str_dieas function.
          Render the corresponding HTML page with the predicted disease and the uploaded image. Run the Flask app.
        End
```

4. Result and Discussion

The existing technique for identifying and categorizing strawberry plant diseases mainly depends on manual diagnosis. Mostly, farmers depend on visual inspection and their knowledge to spot disease signs and symptoms in their crops. This often entails looking closely over the plants to check for lesions, spots, or discoloration, as well as colour, texture, and form changes. Farmers can also search for physical signs like wilting, stunted development, or deformed leaves or fruit. Microscopes, test kits, and imaging devices are a few diagnostic instruments and equipment that can be utilized. However, their availability might be minimized, and their usage may require specialized training and understanding. Many factors, including the farmer's degree of expertise, the standard of the diagnostic equipment, and the complex nature of the disease's signs, might impact the precision of manual diagnosis. Additionally, certain diseases might fail to show signs until they have already seriously damaged the plant, making it challenging to identify and diagnose them [14]. For assistance with identifying diseases and control, farmers may occasionally also engage with agricultural specialists or extension workers (Table 1).

Table 1: Hardware Requirements

No.	Name of the Components	Description
1	Hard disk	PC with 520 GB or more Hard disk.
2	Ram	PC with 8 GB RAM.
3	Processor	Intel(R) Core (TM) i5-1035G1 CPU
4	GPU	NVIDIA

According to our research, not much work is done in strawberry plant disease detection and classification using a weighted ensemble Deep Convolutional Neural Network as the trained model to predict. Some existing software programs such as Plan Tix, Plant Village Nuru, and more applications exist. These applications do not specifically predict the diseases of the strawberry plant diseases and give the cure methods to them. These applications give predictions and cures for only some common diseases. They do not provide the specific and rare disease prediction of strawberry plants. There are some applications

like Crop Tracker and some applications that are mainly used to monitor plant diseases (Table 2). However, they are not proving the disease's predictions and classification. They also do not provide cure methods for diseases.

Table 2: Software Requirement

No.	Description	Type
1	Operating System	Windows XP / Windows
2	Client-Side Technologies	Flask, Python
3	Editor	Visual Studio Code, Spyder
4	Browser	Google Chrome/Firefox
5	Front End Technologies	HTML, CSS, JavaScript, Bootstrap

This paper aims to introduce and develop an application by which the users/farmers can predict the disease of the strawberry plant by giving the image of the leaf/flower/fruit to which part the disease has occurred. The application will describe the cure methods for diseases predicted in the strawberry plant. It also predicts healthy leaves other than diseased ones. This application was also developed to check the pesticide details for the disease and experts/pathologists' details to understand the predicted diseases better. Another feature is that this application will provide the cure methods in three different languages, which will be helpful for the farmers in different places. So, this application provides a single-step solution for all the problems related to strawberry disease prediction and will help the farmers predict and classify the diseases in the early stages and get a better income.

4.1. Problem Analysis

The Developed "Strawberry Plant Disease Detection and Classification Web Application" is a web-based application for predicting and classifying strawberry plant diseases. With deep learning algorithms, the online application can identify and categorize diseases in strawberry plants. The website is designed to support growers and farmers in effectively detecting and managing plant diseases.

- **Disease Detection:** The web app can detect various diseases that affect strawberry plants, such as Powdery Mildew, Leaf angular spot, Gray mould, and Blossom blight. The app can analyze images of strawberry plants and detect the presence of any disease symptoms.
- **Disease Classification:** The web app can classify the detected diseases based on their symptoms and severity. This feature can help farmers and growers identify the specific disease affecting their plants and take appropriate measures to control it.
- **Giving description and cure:** The application will give farmers in various locations a description of the problems of the strawberry plant and treatments for them in three distinct languages.
- **User-Friendly Interface:** The web app has a user-friendly interface that is easy to navigate and understand. The interface provides visualizations and reports on disease prevalence and severity, making it easy for farmers and growers to interpret the data.

4.2. Product Benefits

- **Early Detection:** The web app can detect diseases in strawberry plants early, allowing farmers and growers to take preventive measures and avoid crop losses.
- **Improved Disease Control:** The web app can classify diseases based on their symptoms and severity, allowing farmers and growers to implement appropriate disease control measures. Increased Yield: By detecting and controlling diseases in strawberry plants, the web app can help farmers and growers increase their crop yields.
- **Cost Savings:** The web app can help farmers and growers reduce their costs by minimizing crop losses due to diseases.

Feasibility Analysis: The feasibility study is a critical technique for determining the feasibility of a particular paper or idea. It includes exploring many issues, including technical, economic, legal, operational, and environmental considerations, to evaluate whether the paper is feasible and attainable. The feasibility study aims to estimate the possibility of success and identify any challenges or hurdles hindering the paper's success.

Technical Feasibility: This would involve examining the availability and quality of images of strawberry plant disease datasets. The dataset must be large and diverse to build an accurate model for detecting and classifying diseases. The availability of machine learning algorithms and image recognition techniques that can accurately detect and classify these diseases would

also need to be assessed. The hardware and software requirements for developing, deploying, and maintaining the application will also be a part of this analysis.

Economic Feasibility: This would involve estimating the costs of developing and deploying the application, including hardware, software, and personnel costs. The revenue potential of the application would also need to be assessed. This could include estimating the potential market for the application and the willingness of strawberry plant growers to pay for the service.

Operational Feasibility: This would involve assessing the application's ability to be integrated into the workflows of strawberry plant growers. The availability of the necessary resources, such as personnel, hardware, and infrastructure, to effectively use the application would also be assessed. The application's ease of use and reliability must also be evaluated.

5. Software Requirement Analysis

We have used many technologies in this paper. We have used frontend technologies, HTML, CSS, JavaScript, and Bootstrap.

HTML: HTML is an important language used for developing and organizing web pages. It acts as the Worldwide. A standardized framework provides the web's backbone for presenting the material. Tim Berners-Lee created HTML in the late 1980s. In our paper, we used HTML to create web pages for the web-based application. Using HTML, we have created the home page, Disease Description & Remedies page, Experts page, Pesticides Page, and Contact Us page.

CSS: HTML can be combined with CSS and JavaScript to enhance the visual presentation of web pages. CSS controls the layout, colours, fonts, and overall visual appearance. CSS has multiple style declarations that can be applied to the same HTML element, and the final style is determined by a set of predefined rules, including the order of the styles, the specificity of the selectors, and the use of inheritance. In our paper, we used CSS to style the HTML pages we created in the web-based application. We have applied the CSS to the Home page, Disease Description & Remedies page, Experts page, Pesticides Page, and Contact Us HTML pages.

Javascript: JavaScript is a programming language that has profoundly impacted web development since its introduction in the mid-1990s. It revolutionized how websites were built by enabling dynamic and interactive elements to be added to web pages, bringing a new level of interactivity and responsiveness to the user experience. In our paper, we have applied JavaScript mainly to the "Upload Image" part of the web application. After the user has uploaded the image and clicked on the predict button. The JavaScript works here and interacts with the backend flask and Python to get the prediction.

Bootstrap: Bootstrap also comes with a powerful CSS framework that provides a collection of predefined styles and classes. This makes it effortless to style and customize the appearance of various elements on a web page. In our paper, we used Bootstrap to implement the predefined CSS and JavaScript Frameworks needed to design the web pages. We used Bootstrap for the Home page, Disease Description & Remedies page, Experts page, Pesticides Page, and Contact Us HTML pages.

Python: Python was designed to focus on code readability, emphasizing clean and concise syntax that resembles natural language. This feature makes it easier to write and understand Python code, reducing the chances of errors and enhancing collaboration among developers. We have used Python to design and train the CNN models we used in the paper. We have imported all Python libraries to do the preprocessing, data augmentation, and design of the ensemble model.

Flask: Flask is designed to be a micro-framework, providing the core functionality needed for web development while keeping the framework lightweight and unopinionated. One of the key features of Flask is its routing system, which allows developers to map URLs to functions or methods, enabling the handling of different HTTP requests and defining the application's behaviour. This routing mechanism simplifies the creation of clean and intuitive URLs and facilitates the development of RESTful APIs. In our paper, we used Flask to make the app.py file in which we wrote the code to create the web application. We have implemented the routes to navigate to the different pages on the website. We have created different functions to get the prediction and redirection to the different HTML pages.

6. General Description

The goal of the web application for the early diagnosis and treatment of diseases infecting strawberry plants is to help farmers and plant pathologists. The features and functions of the web application are to be described through this software requirement analysis.

6.1. Functional Requirements

- **Upload Image:** The online application allows Users to upload pictures of strawberry plants showing disease symptoms.
- **Disease Identification:** The online application can identify and categorize the disease in the provided images.
- **Prediction:** To find plant diseases that damage strawberry plants, the online application can give predictions of the diseases.
- **Treatment Recommendations:** The online application gives the user information about the disease that has been found, including any potential causes, signs and symptoms, and suggested procedures.
- **Experts Contact:** Users of the web application can contact plant professionals or extension officials for more help in managing the diseases and to get suggestions from them.
- **Pesticides Information:** The web application can provide information about pesticides that can cure different strawberry plant diseases and help decrease the loss.

6.2. Non-Functional Requirements

- **Reliability:** The web application can accurately detect diseases and deliver precise and reliable results for various strawberry plant diseases.
- **Availability:** There shouldn't be much downtime for maintenance, and the application should be highly available.
- **Performance:** The application has less latency and quick reaction times to user input upload, Image processing, and prediction. The application should be able to produce predictions quickly and efficiently.
- **Scalability:** The web application can be scalable and capable of handling high user traffic and picture-uploading volumes.
- **Usability:** The web application must have a simple, user-friendly interface for the farmers/users to use and understand. They can easily navigate to the different parts of the web application.

6.3. Xception Model

We have applied the transfer learning on the exception model and added the required custom layers. After that, we trained the exception model for 20 epochs with batch size 16 and a learning rate of 0.001 (Figure 7). We recorded the values of accuracy and loss at each epoch and plotted the validation and training graphs for the model (). The graphs below show the exception model's training and validation accuracies and losses (Figure 6).
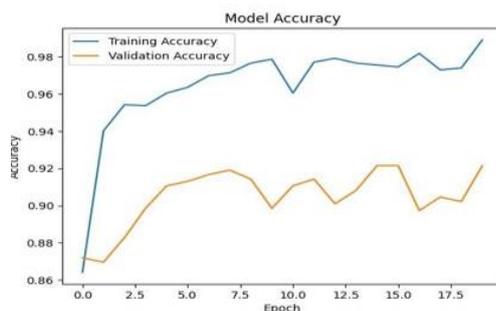

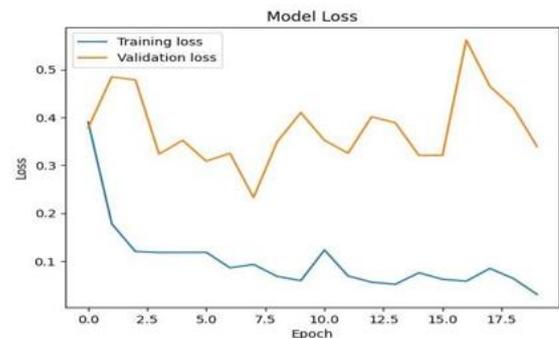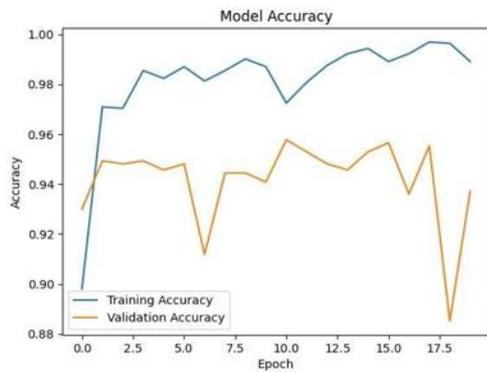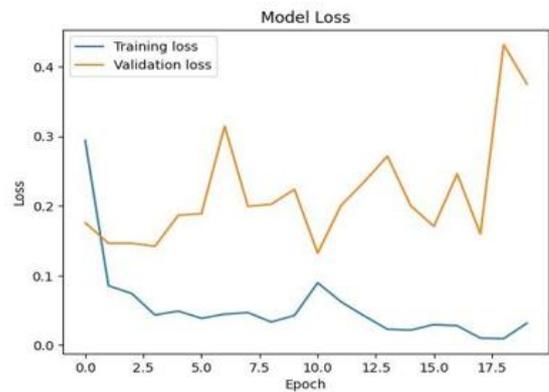**Figure 6:** Model accuracy for exception

Figure 7: Model Loss for exception

6.4. DenseNet169 Model

We have applied the transfer learning on the DenseNet169 model and added the required custom layers. After that, we trained the DenseNet169 model for 20 epochs with batch size 16 and a learning rate of 0.001 (Figure 9). We recorded the values of accuracy and loss at each epoch and plotted the validation and training graphs for the model. The graphs below show the training and validation accuracies and losses of the DenseNet169 model (Figure 8).

**Figure 8:** Model Accuracy for DenseNet169

Figure 9: Model Loss for DenseNet169

6.5. MobileNet Model

We have applied the transfer learning on the MobileNet Model and added the required custom layers. After that, we trained the MobileNet model for 20 epochs with batch size 16 and a learning rate of 0.001 (Figure 10). We recorded the values of accuracy and loss at each epoch and plotted the validation and training graphs for the model. The graphs below show the training and validation accuracies and losses of the MobileNet model (Figure 11).
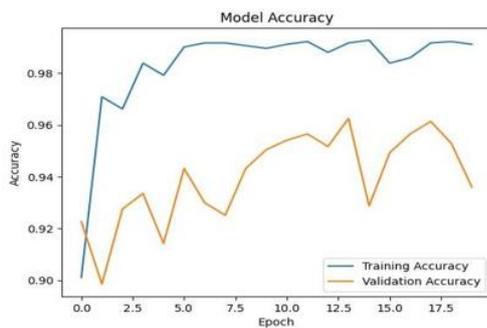
Figure 10: Model Accuracy for MobileNet
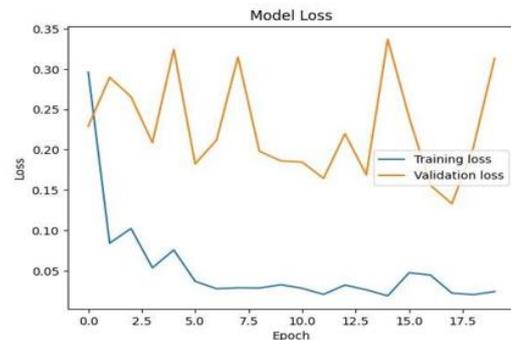
Figure 11: Model Loss for MobileNet

7. Conclusion

This study presents a robust and efficient approach for early and accurate detection of diseases in strawberry plants using deep learning techniques. By leveraging transfer learning with pre-trained convolutional neural network (CNN) models—specifically Xception, DenseNet169, and MobileNet—we successfully developed a system capable of identifying plant diseases from image data with high accuracy. The incorporation of an ensemble model further improved classification performance by combining the strengths of individual models, demonstrating the value of integrated learning in agricultural diagnostics. Our methodology not only enhances the precision of disease detection but also significantly reduces the time and effort involved in traditional practices such as manual inspection and laboratory testing.

The deployment of the trained models into a user-friendly web-based application makes this solution practical and accessible for real-world agricultural use. Farmers can upload images of their crops and instantly receive disease diagnoses along with treatment suggestions, empowering them to take timely and informed action. The experimental results validate that deep learning, when integrated into a smart application, holds significant potential for transforming traditional farming methods into technology-driven practices. This system not only minimizes crop loss due to late or incorrect diagnosis but also promotes sustainable agriculture by enabling targeted disease management. In conclusion, the proposed AI-driven framework contributes to the advancement of precision agriculture, offering a scalable and cost-effective tool for improving crop health and productivity. Future enhancements may include expanding the system to detect a broader range of crops and diseases, further strengthening its impact on global agricultural practices.

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