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Plant Leaf Disease Detection Using Xception Model

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***Abstract:** The traditional farming practices have been causing significant financial losses to farmers due to various reasons. However, the implementation of a modern, smart agricultural system utilizing machine learning techniques appears promising in safeguarding farmers and traders against these risks. This advanced system facilitates farmers in identifying common diseases through simple image recognition, employing a variety of image processing methods. Notably, the Convolutional Neural Network (CNN) algorithm stands out as an effective choice among these methods. Interestingly, among the available models, there has been limited utilization of the Xception model, and no comprehensive comparative study involving this model with different classifiers was found. To address this gap, a study was undertaken in two distinct approaches. Firstly, the Xception model demonstrated remarkable accuracy in detecting plant diseases, achieving an impressive 98.3 percent accuracy rate. In comparison, other classifiers such as logistic regression and three additional methods attained accuracy rates of 93 percent and 92 percent, respectively. Secondly, a comparative analysis was conducted on the top 12 papers out of a selection of 45 papers, each employing different methods. The Xception method once again proved to be effective in this context. Through these tests and review studies, the Xception method emerged as a reliable and superior choice. It is expected that this research will provide valuable insights for researchers and stakeholders, potentially guiding the development of new research initiatives in this field.*

***Keywords:** Convolutional Neural Network, Xception, Deep Learning, Logistic Regression, Decision Tree.*

1. INTRODUCTION

Challenging the conventional agricultural practices, the contemporary approach is increasingly favoring modern agricultural methods. In today's era, machine learning is gaining significant

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traction. Among the diverse techniques employed to enhance the efficiency of global agriculture, image processing through evolutionary neural networks holds a prominent place. Determining the type of disease from a plant's leaf photograph is a complex task. However, leveraging various machine learning-based image processing methods makes it feasible to discern different diseases. When a farmer can employ their device to diagnose various symptoms present on the leaves, it expedites the treatment of plants and ultimately augments productivity within the agricultural system.

Smart farming has embraced the application of machine learning to address data-intensive tasks within the realm of agriculture. These tasks encompass a wide range of activities such as data collection, analysis, monitoring, and predictive modeling. Additionally, machine learning has played a pivotal role in advancing agricultural research by examining farming practices aimed at optimizing resource utilization and adapting to changing climate conditions. This, in turn, has contributed to enhancing the quality and yield of agricultural produce.

Furthermore, machine learning technologies have facilitated the automation and computation required for large-scale farming operations. Notably, they have been employed in plant classification systems designed to forecast farm yield and identify diseases and defects in crops. Machine learning has also been instrumental in addressing various agricultural challenges.

The proposed Convolutional Neural Network (CNN) model has demonstrated remarkable success in accurately identifying plant images, achieving an impressive accuracy rate of 99.88%. Future endeavors will involve the expansion of the existing image database to encompass a broader range of plant images. Moreover, efforts will be directed towards integrating this system into the development of a robotic harvesting system tailored for orchard plants[1]. The Xception model is highly effective in preventing overfitting while maintaining spatial information, resulting in improved classification performance. Among all the classifier combinations tested, Xception consistently delivered the best results across different exaggeration factors, making it a leading technique for binary classification of breast cancer histopathological images in the current setup. It may be worth exploring a hybrid ensemble model that integrates a pre-trained Xception model to assess its influence on classification outcomes. Furthermore, combining a pre-trained Xception model with a Bi-LSTM deep neural network could offer a promising approach to tackle binary classification challenges.[2].

Even in the present day, farmers heavily rely on agronomists to address the numerous challenges associated with their crops, especially when it comes to plants, which are highly vulnerable to diseases. The absence of agronomists at critical times often results in plant crops becoming infected. If farmers could utilize a device to independently identify diseases from leaf and other plant part photographs, as well as receive treatment recommendations, they would be spared from annual losses amounting to millions of rupees. Several challenges had to be tackled to facilitate the automatic identification of plant types from camera images. Numerous plants exhibit substantial variations in terms of their shape, texture, and color, which can change depending on their ripeness. For instance, consider the apple, which can transition from green to yellow or develop a patchy brown appearance. Relying solely on a single image descriptor for accurate classification may not suffice. Consequently, it becomes essential to extract and amalgamate features that are pertinent to the recognition of plants and vegetables, addressing this particular problem effectively. In certain scenarios, the object under analysis might be enclosed within a plastic bag, potentially introducing distortions in terms of color and

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reflections. The inspection and grading of plants and vegetables for quality and safety are typically carried out by certified inspectors. However, inconsistencies in their evaluations can result in significant wastage or suboptimal purchases. Each false positive decision contributes to a poor purchase, while false negatives lead to unnecessary waste. These challenges have contributed to a situation where only approximately 60% of produce in the United States successfully reaches the market from the farm[3]. Numerous research papers have delved into image processing, yet the detection accuracy rates have exhibited variations across these studies. Additionally, the practical effectiveness of implementing this technology in real agricultural systems remains a matter of concern. The limited access to information and knowledge, especially in a country like Nepal where agriculture is the main source of income, has contributed to this problem. As a result, we are initiating research in this field to investigate and tackle these complex challenges, based on the conviction that research in this area is both necessary and justified. What was once deemed impossible now appears attainable in today's context. This research endeavors to explore plant-related inquiries using photographic data. Within this study, specific research questions have been formulated. Firstly, among the diverse convolutional neural network models, does the Xception model outperform other classification methods in terms of accuracy percentage? Secondly, when compared to the results documented in the reviewed literature, does the Xception method exhibit superior efficacy in disease detection based on symptoms observed on plant leaves? The main objective of this study is to identify different plant leaf diseases by determining the most effective method, using image processing and machine learning techniques. The objectives serve as the guiding principles for our research, ensuring that our investigation remains focused and purposeful. Research devoid of a clear aim can easily veer off course. Although this research covers a wide range of topics, its primary focus is on image processing. The specific research objectives are: first, to perform a comparative analysis of the accuracy of the Xception model, a type of Convolutional Neural Network (CNN), against other classification methods; and second, to compare the accuracy of various techniques discussed in research papers with the results obtained using the Xception model presented in this study. This research endeavors to offer solutions to these issues, underlining its importance areas; the facilitate the identification of different types of diseases in plants through the use of photographs. It strives to detect issues in various plants that may go unnoticed by the naked eye. The research aspires to empower ordinary individuals to recognize and address various plant diseases using photographs, thereby enabling them to administer necessary treatments.

To streamline and simplify this research, specific boundaries and constraints have been established. The research will primarily involve the identification of plants using photographs of the plant itself, as well as images of plant seeds and plant symptoms to detect various diseases. It's important to note that this study exclusively utilizes the Kaggle dataset. The experimentation is limited to the Xception model, Logistic Regression classifier, and Decision Tree classifier. Furthermore, the identification of various plant diseases will solely rely on photographs of plant leaves, with no inclusion of other plant parts. Moreover, this research will not include the use of all available image segmentation algorithms or cover every type of disease detection method. The main contribution of this study lies in applying automatic image processing within the agricultural sector. The work presented can be utilized to design automated systems for agricultural processes using images from remote farm fields. This project on plant disease detection through image processing offers several potential contributions. Early detection of plant diseases is crucial for preventing their spread and reducing crop losses. Image processing techniques can enhance the accuracy of disease detection compared to traditional methods. Additionally, this research can contribute to the development of new image processing techniques and algorithms.

2. RELATED WORKS

Reviewing academic papers comes with its own challenges. To strengthen the credibility and effectiveness of this research, a thorough analysis was carried out by carefully examining papers written by different researchers. During this search, a mix of pertinent and irrelevant papers were identified. Here is a summary of the papers reviewed.

A cutting-edge technology called the smart farming system has been developed to boost agricultural productivity, specifically targeting tomato cultivation. This advanced system utilizes key infrastructure to enhance both the quality and quantity of crop yields. It employs a Convolutional Neural Network (CNN) to detect diseases in tomato plants. By automating image capture and analysis, the system achieved a remarkable 91.67% accuracy in identifying diseases on tomato plant leaves.[4].

Agriculture plays a crucial role in our society, yet farmers often struggle to accurately identify leaf diseases, leading to lower crop yields. The researchers utilized a publicly available dataset containing 5,000 images of both healthy and diseased plant leaves. Using semi-supervised methods, they aimed to identify crop types as well as detect four different categories of diseases[5].

The research paper focuses on five specific apple leaf diseases: area leaf spot, brown spot, mosaic, grey spot, and rust. The test results reveal that the proposed INAR-SSD model delivers a strong detection performance of 78.80% and a rapid detection speed of 23.15 frames per second (FPS). This highlights the effectiveness of the INAR-SSD model for early diagnosis of apple leaf diseases, providing real-time detection with higher accuracy and faster processing compared to earlier methods[6].

The researchers trained a convolutional neural network (CNN) model using a large open dataset containing over 39 distinct classes of plant leaf diseases, along with background images. The simulation results showed an impressive classification accuracy of 96.46% for the proposed model, highlighting its effectiveness. Notably, the CNN model outperformed transfer learning approaches in terms of accuracy[7].

This research paper includes a variety of agricultural images, such as vegetables, plants, crops, and flowers, specifically aimed at identifying leaf diseases in these products. After identifying these features, they are used with a Probabilistic Neural Network (PNN) classifier to detect the presence of diseases. The study utilized a dataset of randomly gathered leaf images from different plants available online[8].

Agriculture has evolved beyond its traditional function of simply providing food for a growing population. The process now involves several stages, including image acquisition, pre-processing, segmentation, feature extraction, and classification, all designed to aid in disease detection. Identifying plant diseases depends on leaf images, and the use of image processing techniques plays a crucial role in detecting and classifying agricultural diseases [9]. Plant

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diseases pose a significant threat to crop production, jeopardizing food security and causing economic difficulties for farmers. To facilitate classification, a variety of features are utilized, such as GLCM, Gabor, and color attributes. The experimental results clearly indicate that the fusion method using a Probabilistic Neural Network (PNN) classifier outperforms other methods in terms of both accuracy and efficiency[10]. In the field of machine learning for plant disease detection, segmenting the affected areas in images of plant leaves is crucial. Textural and color features were extracted and used to develop a linear classifier. A comparative analysis of the classification results emphasizes the advantages of the proposed method, especially in extracting features of dissimilarity. This research opens avenues for obtaining more refined characterization features, thereby improving the accuracy of plant disease classification and severity assessment [11].

The issue of global food security has become an important area of research. This study employs the NAS-Net architecture for convolutional neural networks. The model is trained and tested using the publicly available Plant Village project dataset, which includes a wide variety of plant leaf images, each displaying different levels of infection and various locations on the plants. Remarkably, the model achieves an accuracy rate of 93.82%[12].

Tomatoes, a popular vegetable, provide significant health benefits. This study utilizes the extensive Plant Village dataset, which contains 54,306 images of 26 diseases across 14 different crops. The proposed methodology includes three main stages: data acquisition, pre-processing, and classification. The results of this approach are particularly noteworthy, achieving an accuracy rate of 95%[13]. While the aforementioned papers appear promising, it's important to note that not all of them offer comprehensive insights. Specifically, although various CNN methods have been explored in these papers, there is a conspicuous absence of any study utilizing the Xception method. Upon reviewing papers sourced from diverse databases, it became evident that while the Xception method has been employed sparingly, its performance has not been rigorously evaluated. This research endeavors to bridge this gap by assessing the accuracy of the Xception method and exploring avenues for further investigation. It's worth noting that, to the best of my knowledge, no prior comparative studies involving the Xception method, logistic regression, and decision tree classifiers have been conducted. Hence, this study seeks to fill this void in the existing research landscape.

3. METHODOLOGY

The research methodology employed in this study is geared towards achieving specific research objectives. To maximize the effectiveness of this research, the initial step involved gathering data pertaining to the issues within the study area. Following this, a research design was formulated, outlining the approach to address the identified problems. With the research design in place, data collection methods were subsequently devised and executed. The amassed data underwent thorough analysis, culminating in the preparation of a comprehensive report. Finally, the entire research process was meticulously documented. The overarching research methodology encompasses these key stages.

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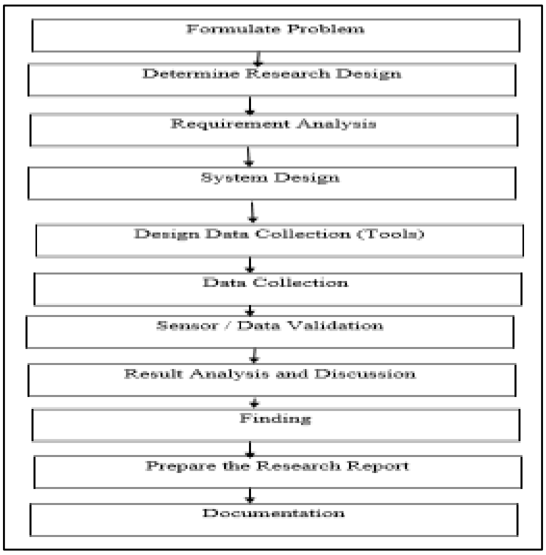

Figure: **Error! No text of specified style in document.**1 (Research Design)

The research work involved the creation of two distinct design approaches. Firstly, data sourced from the Kaggle dataset, specifically plant leaf images, was subjected to CNN (Convolutional Neural Network) analysis. Within this framework, separate methodologies were developed for image processing tasks, focusing on the utilization of the Xception model. Secondly, the research encompassed a comparative analysis of various models, evaluating the tasks outlined in collected research papers.

Conceptual Framework

For the experimental testing in this study, the Python programming language was used in Jupyter Notebook and Google Colab. The accuracy was assessed by training the collected samples. The methodology of this study is outlined as follows.

Figure: 2 (Conceptual framework)

Data

Data is important in research because it can be used to hypotheses, identify patterns and trends, measure and quantify phenomena, generalize findings, and support decision making. The

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quality of the data collected and analyzed is critical to the validity and reliability of research findings.

This research project utilized two types of plant leaves: healthy and diseased. The diseased leaves include those affected by rust, scab, and multiple diseases. The data was sourced from Kaggle, totaling 3,651 leaf images. Specifically, there are 1,399 images of rust, 1,200 images of scab, 187 images showing multiple diseases, and 865 images of healthy leaves, all in JPG format. A pie chart illustrating the distribution of these images is provided below.

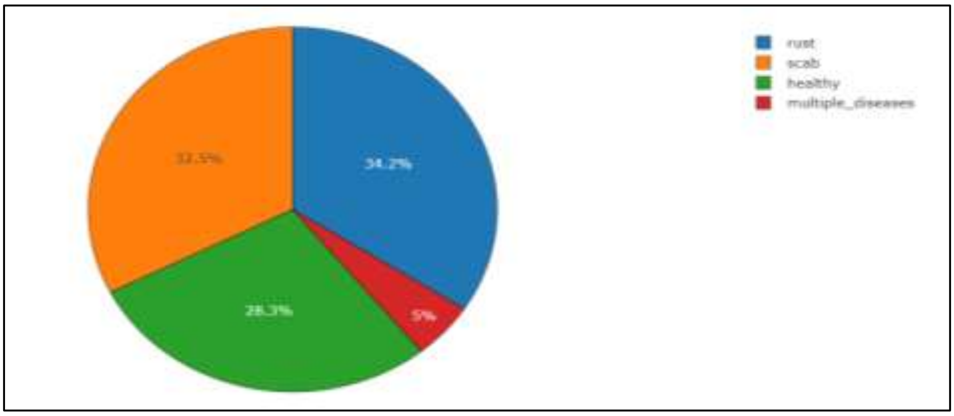

Figure: 3 (Pie-chart of Data)

In cases where the leaves are severely damaged, treatment becomes very challenging. Our dataset contains only 5% of images from such cases.

Figure: 4

Image Processing

The downloaded photos for this research initially measured 2028 x 1328 pixels but were resized to 299 x 299 pixels. Additionally, 1,421 images were randomly selected from the total of 3,651. Of these, 1,000 were designated for training and 421 for testing, representing a distribution of 70% for training and 30% for testing.

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Color Conversion
All photos were converted to BGR format. RGB stands for Red, Green, and Blue. Typically, an RGB color is stored in a structure or unsigned integer, with Blue being the least significant, followed by Green, and Red in the most significant position. Conversely, in some platforms, a BGR model is employed, but RGB is more commonly used on systems like ours. OpenCV supports the BGR format.

Model Development
This study employs a CNN model, which is a widely used algorithm in deep learning. Within this category, the Xception model is specifically utilized.

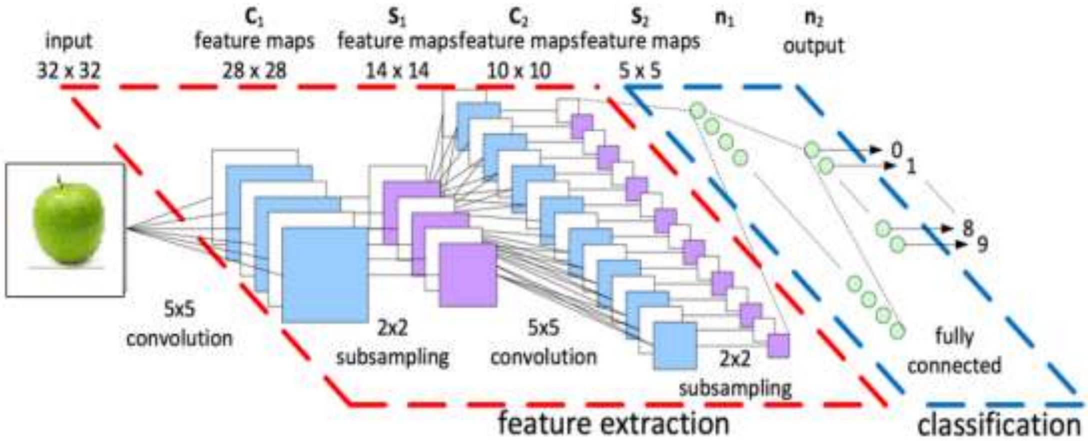

Figure: 5 (CNN Model) (source[1])

Implementation and Training
The proposed technique was implemented in Keras, built on TensorFlow, using a workstation with 8 GB of RAM and an Intel(R) Core(TM) i5-10300H CPU @ 2.50GHz processor, as well as Google Colab with GPU support. The model was trained on a prepared dataset using Python. In this project, a batch size of 16 was used, along with 1,000 epochs. The training and validation losses of the proposed model converged after approximately 15 epochs.
The Xception model is a deep convolutional neural network introduced by Francois Chollet in 2016. It is built on the Inception architecture, utilizing a series of parallel convolutional layers with varying filter sizes to capture features at multiple scales. However, instead of employing traditional convolutional layers, the Xception model utilizes depthwise separable convolutions, which are more efficient and capable of capturing more complex features. The Xception architecture comprises 36 convolutional layers that serve as the feature extraction foundation of the network[14].

4. RESULTS AND DISCUSSION

To evaluate the results of apple leaf disease detection using the Xception model, we first need a dataset of apple leaf images labeled to indicate whether they have scab, rust, multiple diseases, or are healthy. Once we have this dataset, we can train the Xception model using

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supervised learning. Accuracy reflects the ratio of correctly classified samples, while precision indicates the proportion of true positive classifications among all positive classifications. Recall measures the proportion of true positives out of all actual positives, and the F1 score is the harmonic mean of precision and recall. After training and evaluating the Xception model, we can analyze the results as follows:

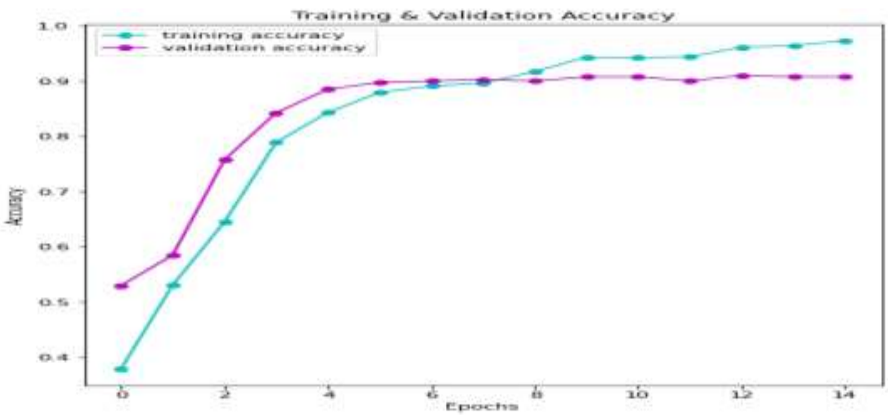

Figure: 7 (Training and validation accuracy)

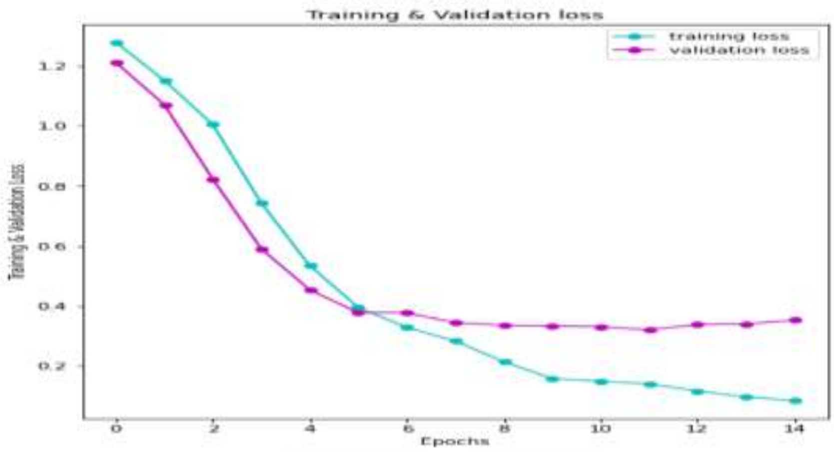

Figure: 8 (Training and Validation loss)

Here's a general outline for conducting an experiment and analyzing results using the Xception model for plant disease detection. First, gather a dataset of apple leaf images and label them according to whether they exhibit scab, rust, multiple diseases, or are healthy. Then, calculate the Accuracy, Precision, Recall, and F1 score for each disease class to gain a deeper understanding of the model's performance. For instance, if the model shows high precision but low recall for a specific disease class, it indicates that while it accurately identifies the disease when present, it may overlook some cases.

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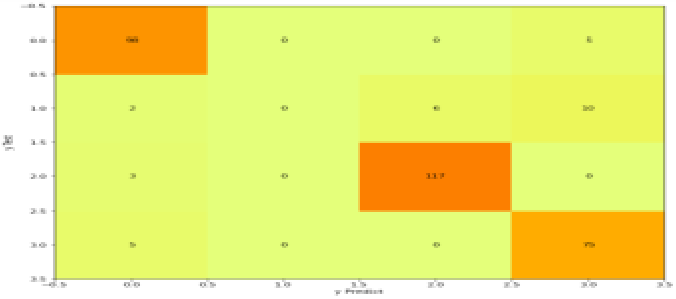

Figure: 9(Confusion Metrics of Xception Model)

With the help of confusion metrics, the results of accuracy, precision, recall and F1 score have been calculated as follows.

Plants Leaf Types	Precision (%)	Recall (%)	F1_Score (%)
Healthy Leaf	90	91	91
Multiple Disease Leaf	0	0	0
Rust Leaf	96	99	97
Scab Leaf	86	92	89

Table No: 4. 1 (Result Analysis of Xception Model)

The accuracy of train image is: 98%
A comparative analysis of various machine learning models for detecting plant leaf diseases can help us determine the most effective method for this task. In this study, we compared the performance of the Xception model, Logistic Regression, and Decision Tree models using image processing techniques for plant leaf disease detection. Conducting this comparative analysis necessitates careful attention to the dataset, preprocessing methods, evaluation metrics, and experimental setup. By evaluating the performance of these models, we can identify the most effective strategy for detecting plant leaf diseases.
Precision is a performance metric utilized to assess the accuracy of a classification model in detecting plant leaf diseases through image processing. It measures the proportion of true positive predictions out of all positive predictions made by the model. Essentially, precision reflects how many of the predicted positive cases are genuinely positive. In the context of detecting fruit leaf diseases, precision can be defined as follows:

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

Precision is defined as the number of true positives divided by the total number of positive predictions.

Plant Leaf Types	Xception	Logistic Regression	Decision Tree
Healthy Leaf	90	93	71
Multiple Diseases Leaf	0	16	4
Rust	95	97	95
Scab	86	98	86

Table No: 2(Precision analysis of Xception, Logistic and Decision Tree Model)

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Recall measure the percentage of correctly classified diseased images out of the total number of diseased images.

Recall = $\frac{True\ Positive}{True\ Positive+False\ Negative}$

Plants Leaf Types	Xception	Logistic Regression	Decision Tree
Healthy	91	98	82
Multiple Diseases	0	35	24
Rust	99	95	81
Scab	91	91	71

Table No: 3 (Recall Analysis of Xception, Logistic and Decision Tree Model)

The F1 score is a metric that combines precision and recall into a single score to assess the overall performance of a classification model. In the context of detecting plant leaf diseases through image processing, the F1 score can be calculated for each relevant class to evaluate the model's effectiveness in accurately classifying each type of leaf disease. It effectively summarizes the predictive performance of a model by integrating these two competing metrics.

F1- Score = $\frac{2*Precision*Recall}{Precision+Recall}$

Plants Leaf Types	Xception	Logistic Regression	Decision Tree
Healthy	91	95	77
Multiple Diseases	0	22	7
Rust	97	96	89
Scab	98	96	78

Table No: 4 (F1- Score Analysis of Xception, Logistic and Decision Tree Model)

The accuracy of detecting plant diseases through image processing can vary based on several factors, including the quality of the images, the algorithms employed, and the expertise of those who develop and train the model. Overall, the accuracy of plant disease detection using image processing can be quite high. Numerous studies have demonstrated that machine learning algorithms and deep learning neural networks can achieve accuracy rates exceeding 90% in identifying different plant diseases.

Accuracy = $\frac{No.of\ images\ correctly\ classified}{Total\ no.of\ images}$

Xception	Logistic Regression	Decision Tree
98%	93.3%	77.64%

Table No: 5 (Accuracy Analysis of Xception, Logistic and Decision Tree Model)

Accuracy is a widely used metric for assessing the overall performance of a classification model in detecting plant leaf diseases using machine learning. It quantifies the proportion of correctly classified samples relative to the total number of samples. The Xception model achieved the highest accuracy of 98%, meaning it correctly classified 98% of the samples. The results are illustrated in the diagram below.

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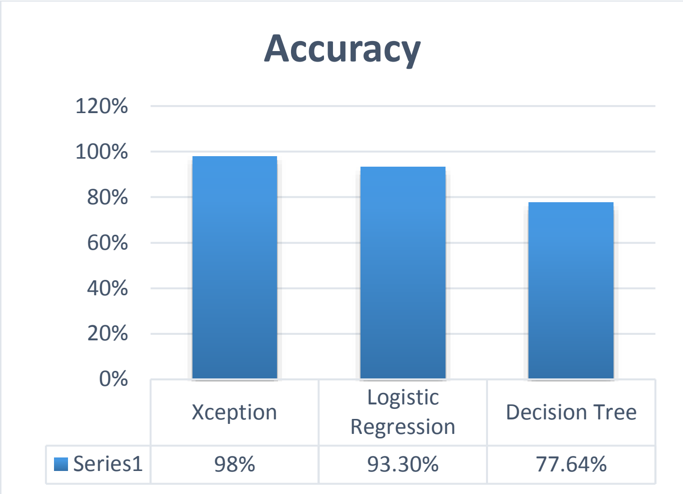

Figure: 10 (Diagram of Xception, Logistic Regression and Decision Tree Model)

The study is crucial for ensuring reliability and validity. Numerous research papers were reviewed to enhance credibility. The process of paper selection and methodology is detailed in the third chapter. From the literature review, four papers were chosen using a random sampling method, and the accuracies reported in those papers are presented below.

Paper	Title	Model	Accuracy
1	Identification of plant leaf diseases using a nine layer deep convolutional neural network	Nine layer Deep CNN	96.46%
2	GUI based Detection of Unhealthy Leaves using Image Processing Techniques	SVM and ANN	85% and 97%
3	Deep Learning Based on NAS Net for Plant Disease Recognition Using Leave Images	CNN (NAS-Net)	93.82%
4	Tomato Leaf Disease Detection using Convolutional Neural Networks	CNN (KeNet)	95%
5	Our Research	Xception	98%

Table No: 6 (Validation Analysis of Difference paper and Xception Model)

The research project on plant disease detection using image processing seems to have achieved promising results. The use of advanced deep learning models like Xception model has resulted in a very high accuracy rate of 98%. The high accuracy of Xception can be attributed to its deep architecture, which is trained on a large dataset and is capable of detecting even subtle variations in the images. Finally, this research has compared to accuracy of various model for fruits disease detection using image processing. The result suggests that deep learning models like Xception, Ke Net, and NAS-Net can achieve accurate rates, while traditional models like SVM and ANN can also perform well, the accuracy rates achieved by each model can depend on several factors, including the size and quality of the dataset, the complexity of the task, and the model's architecture. While examining the accuracy of various papers that utilized different models and methods, it was demonstrated that the accuracy percentage I obtained is higher, confirming that the Xception model ranks among the top models.

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5. CONCLUSION

Farmers relying on traditional agricultural systems incur losses amounting to crores of rupees each year. In contrast, modern agriculture, particularly smart agricultural systems leveraging machine learning, has the potential to mitigate risks for farmers and traders. However, there has been limited use of the Xception model and a comparative analysis of this model with different classifiers. Therefore, a study was conducted on this topic in two ways. First, the accuracy of plant leaf images collected from Kaggle was evaluated using the Xception model, achieving an impressive accuracy of 98.3%. In comparison, logistic regression and decision tree methods yielded accuracies of 93% and 92%, respectively. Second, among the 45 papers reviewed, a comparative analysis of the top 12 papers using various methods was performed, with the Xception model also proving effective. Based on the tests and review studies conducted, the Xception model is deemed excellent and highly reliable. This research is expected to assist researchers and relevant stakeholders in planning future studies.

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