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CORN LEAF DISEASE PREDICTION USING DEEP LEARNING

Meghana Varayuri

CORN LEAF DISEASE PREDICTION USING DEEP LEARNING

A Project

Presented to the

Faculty of

California State University,

San Bernardino

In Partial Fulfillment

of the Requirements for the Degree

Master of Science

in

Information Systems and Technology

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by

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ABSTRACT

Corn is a widely cultivated agricultural product, serving as a cornerstone in food production and industrial applications such as biofuels, playing a crucial role in the global economy. This study explores the application of deep transfer learning to accurately classify major corn diseases from leaf images, aiming to enhance disease management strategies for improved agricultural productivity and sustainability. The research questions are as follows: (Q1) What is the efficiency and effectiveness of deep learning systems for identifying and classifying diseases of corn leaves using images? (Q2): How does using data augmentation methods affect Deep Learning's model performance while detecting corn leaf disease using images? (Q3): Can the accuracy of detecting corn leaf diseases using images differ from using various optimizers, such as Adagrad, SGD, AdaDelta, and Adam? The findings are: (Q1) The customized Dense net 201 model achieved 95% prediction accuracy on an untrained dataset. (Q2): Data augmentation improved the model's accuracy from 91% to 95%. This supervised learning approach enhances the model's performance by increasing the diversity, leading to better generalization and accuracy. (Q3): Experimentation of the four optimizers, namely Adagrad, SGD, AdaDelta, and Adam, achieved the same accuracy (95%). The conclusions are (Q1): Increasing the data by a significant margin leads to a considerable enhancement of the model from 91% to 95% and thus serves as evidence of the effectiveness of the proposed method in improving the model performance, therefore improving the

generalization samples for better training samples. (Q2): It is testified that even the optimizer selection influences the accuracy rate.

AdaDelta and Adagard achieved the highest accuracy at 95%, emphasizing the importance of selecting the right optimizer for optimal performance. (Q3): The optimized deep learning model achieved 95% accuracy in detecting and classifying corn leaf diseases, benefiting farmers in disease identification. In conclusion, data augmentation significantly improves deep learning model accuracy by diversifying training samples, and the choice of optimizer is crucial for optimal performance. AdaDelta and Adagrad yielded the highest accuracy rates, emphasizing the importance of these techniques in developing effective models for detecting corn leaf diseases. Future researchers should explore various stages of diseases using advanced deep learning models such as ResNet, EfficientNet, and Vision Transformers (ViTs) as part of their investigations.

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DEDICATION

I would like to dedicate this project to my parents, Prameela and G.V. Narsaiah who gave their support and encouragement to fulfill my Master's dream. They dreamt of me. Through this path, I have always found strength and inspiration in their unwavering support, endless sacrifices, and unlimited love. You and I both share equal credit for this accomplishment. Also, I would like to give a special shoutout to my husband, Raghuram Varayuri. I am grateful for your unwavering support, tolerance, and faith in me, even in the most trying circumstances. To my daughter, Aikya Varayuri, whose happy grins, warm embraces, and pure delight have inspired me and served as a daily reminder of what is truly significant.

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CHAPTER ONE:

INTRODUCTION

Since the Neolithic period, corn has been an essential part of civilized society and still exists today. Because of technological advancements in farming, corn has become one of the most widely grown crops globally. Studies on corn have also increased as it is one herbaceous crop whose importance is well recognized (Daneshwari et al.,2022). Maize has taken a central place in the agricultural world because the population has grown, and as a result of this, the demand for food has dramatically risen. Corn and other cereal grains, such as wheat and rice, are some of the most consumed food sources for humans. For instance, Asia is the largest producer and consumer of rice, constituting about 21% of per capita calorie intake as per the reports of FAO of 2013.

On the other hand, corn is a food crop grown in many places, especially in the Americas, and is used directly by people and farmers as livestock feed. The US was the leading producer in the world, with 333 MMT of maize produced in 2010. Global production was comprised of as follows 40%—4% of the worldwide output. Mekouar (2015) asserted that other major international producers, including China, Brazil, and India, are seen as essential in feeding the world's increasing population, aside from playing a core role in animal feed production. Although the latter crop is necessary, it remains to be discovered in scholarly literature (Daneshwari et al.,2022). Therefore, diseases that may affect this plant may reduce production and, in turn, influence developing countries' economies (Yujin et al.,2019).

Given this, it needs to be understood that crop losses and food security issues can only be managed well if common rust and other diseases affecting corn crops are accurately detected and diagnosed as early as possible. Increasing the accuracy level by applying the replication study using improved methodological tools is feasible. For example, deep learning involving sophisticated approaches could solve issues, which include elements of backgrounds in the natural environment, while those in datasets are usually similar.

Also, enlarging the training dataset containing various images of different types of corn diseases, such as Stewart's Bacterial Wilt, will increase the reliability of the detection system. In addition, for field use, the deep learning models shall be constantly retrained to retain high fidelity and eliminate problems that affect deep learning, such as catastrophic forgetting. This approach ensures that the developed systems are applicable in the real world and benefit agriculture sustainability and food security. Li (2021) and Mishara et al. (2020) point to the recovery nature of disease management by counting agriculture, showing that specific signs like discoloration and lesions require immediate detection so that measures can be taken to eliminate the disease. Furthermore, Saeed et al. (2020) proves that technological advances allow for the formation of automated diagnosing illness systems through machine learning trends for precise and effective treatment methodologies. The existing research activities aim to enhance disease monitoring and trend control by virtually adopting various cross-disciplinary techniques and harnessing technological solutions that benefit farmers and agro teams worldwide.

Identifying various diseases can take time, or carelessness can lead to wrong identification (Yujin et al.,2019). Sample examination using hands is something that is required to be done in traditional methods of diagnosing given disorders. On the other hand, non-traditional approaches, such as automated picture analysis, have already been developed in practice. Optimizing their solutions is the current problem in how to determine these techniques more accurately. This research aims to assist plant pathologists and farmers in getting more accurate and precise diagnoses by using deep transfer learning techniques on a plant's disease dataset. The plant's identification of the diseases results in the spread of the infections to the adjacent fields, which affects the yields (Yao et al.,2014). As found in the literature, the methods to detect corn leaf diseases are (Yujin et al.,2019) and (Daneshwari et al.,2022). The conventional method entails the identification of the disease involving the various attributes, usually on the plant leaves, by the experts. Nevertheless, the technique could be more convenient and qualitative, making its diagnosis inaccurate. This ought to be something that technological advancement should be capable of solving.

Background

Corn diseases affecting the leaves have typically been challenging to diagnose due to their symptoms and growth patterns, but technological advancements have led to improved diagnostics. These methods were used to undertake the images of the leaves of the plant using computer vision with machine learning algorithms and computer image processing. They can identify the patterns for the start writing your text here. DLA's first level is justified and has two double-spaced lines or triple spacing before the heading. Pathologies that the diseases in the images represent (Yujin et al.,2019). From this, one can differentiate diseased from healthy leaves through features like their texture, color, and appearance (Mishara et al.,2020). As much as numerous efforts have been made in the recent past to develop technologies for corn disease detection, particularly those that affect the foliage, many issues need to be addressed (Panigrahi, 2020).

One of these is the impressive progress in large-scale public data availability. This is because developing models for the classification, detection, and evaluation of diseases is challenging, given the need for such data. Apart from the dataset, information such as the progression stage of the tumor and the quality of light that illuminates the image is used to enhance the algorithm. The approach used and adopted by farmers to identify and classify the diseases affecting the maize leaves has evolved with the progression of time, with other mechanized and intelligent ways of doing so. Such solutions stand as improvements to the traditional approaches while offering faster and more accurate solutions with the help of deep learning and image processing. One advantage is that farmers can now quickly assess the status of the crops and detect weaknesses and other issues for possible treatment promptly. Therefore, farmers may reduce loss and eliminate risks through early prevention measures, which ensure enhanced crop production and management (Lamm et al., 2016).

By examining the existing and developed methodologies of these systems, it is understood that the accuracy of detecting diseases can be enhanced even further by harnessing deep transfer learning. This culminating experience project is presented in the following structure. As highlighted in chapter one of the study, this chapter offered an introduction to the study and its background. The literature review and the theoretical framework will be discussed in Chapter 2. It will demonstrate the methods employed to address the research questions in Chapter 3. Specifically, the research is articulated as follows: Chapter 4 Data Collection, Analysis, and Findings. Chapter 5 Discussion, Conclusion, and Recommendation for Future Research.

Problem Statement

Most corn diseases are complex to identify, and this one is no exception; early diagnosis is vital in preventing further spread. This can be done by conducting visual screenings, which entails a trained person going through the fields. This method has been used for many years; however, the process has several effects due to the time and energy consumed and the destruction it entails (Saeed et al.,2021). Forecast of diseases is among the most crucial threats affecting corn production. Unfortunately, the public does not pay much attention to handling the diagnoses of these diseases. Knowledge of the modes of attack of the various corn leaf diseases would enable the researchers to provide a better system to identify them. Looking at the different ailments affecting the corn leaves, one can assemble a well-defined and fast means of identifying them.

Modern machine learning has been applied to rank algorithms to identify plant disease diagnostics; however, more effective and precise algorithms are needed. The average accuracy rates that current algorithms offer range from 85 to 90 percent, which means there is a need to take the current concepts and technologies to the next level in terms of accuracy. Applying modern approaches like deep learning or transfer learning may increase the accuracy of disease diagnosis and overall improvement of agricultural practices and optimized crop management.

Other technologies are also needed to ensure the system's efficiency besides machine learning (Durga et al.,2019). Many studies are currently being conducted on developing deep-learning techniques that can help detect corn leaf diseases. This method would allow you to identify patterns in digital images. Existing systems for identifying plant diseases need to provide more accuracy because they rely on large data sets. New models with deep learning capabilities should be created to increase their accuracy and robustness.

Research Questions

1. What is the efficiency and effectiveness of deep learning systems for identifying and classifying diseases of corn leaves using images? (Amin, 2022).
2. How do data augmentation methods affect Deep Learning's model performance while detecting corn leaf disease using images? (Nagaraju, 2022).
3. Can the accuracy of detecting corn leaf diseases using images differ from using various optimizers, such as Adagrad, SGD, AdaDelta, and Adam? (Saleem, 2020).

Justification

Researchers can help farmers reduce their use of hazardous chemicals and pesticides by using predictive modeling to forecast the start and severity of maize leaf diseases. This has a substantial positive impact on the environment. In addition to lowering agricultural pollution, this proactive strategy encourages the growth of sustainable farming methods. Such a study is essential to determining how farming will develop as ecologically friendly farming practices become increasingly important due to consumer and governmental demands. Researchers can offer tailored solutions enabling environmental protection plans and manufacturing with extensive data on diseases and various environmental conditions. The above strategy is all-embracing as it ensures lasting ecological soundness while enhancing the farm's income.

In conclusion, information about corn leaf disease's economic and financial effects is crucial for developing a long-term and profitable business. It can also positively impact food availability, accessibility, affordability, and nutrition for consumers. This is because early identification of corn leaf diseases will help to avoid significant losses, thus ensuring that its supply is regular and as expected by consumers. This, coupled with price stability, has the effect of minimizing losses for the entire industry. Therefore, it is necessary to perform this research, and it must be done to contribute to the sector's development.

CHAPTER TWO:

LITERATURE REVIEW

Deep learning is one of the most versatile technologies in agricultural science, especially in the differentiation of diseases of maize plants through images. The levels of technique innovation in this new pragmatic approach involve using Artificial Neural Networks (ANNs), Convolutional Neural Networks (CNNs), and other sophisticated machine learning techniques to achieve those improvements in precision agriculture. The subsequent literature review analyses several studies that portray the effectiveness of deep learning models in this area. These studies use methods like ANN and SVM algorithms, CNN frameworks, and transfer learning to improve the identification of maize diseases. Also, the effects of optimizers on models and how to combine fusion approaches for classifier optimization are considered. Both studies offer comprehensive outlooks on how deep learning can transform the approaches to disease management in the agricultural field and support the development of more efficient programs for crops' health and sustainability of agricultural practices.

Q1. What is the efficiency and effectiveness of deep learning systems for identifying and classifying diseases of corn leaves using images?

Kanaka Durga et al. (2019) also utilized ANtheand SVM algorithms to classify various diseases affecting corn and tomato leaves. These consisted of familiar healthy imagery and images of unhealthy leaves, which are the diseased sections, e.g., blights and bacterial stains. To determine the kind of diseases present, the researchers first had to change the color gradient of the image into the Black and White image. They later determined the intensity of the pixel for each of the pixels in the image to segment it. They then extracted the features using SIFT and HOG to get the data before training. The researchers then used two classifiers to train them on the basics of the extracted features. The evaluation of the model showed that the SVM model developed could classify patent documents with an accuracy rate of approximately 75 percent. In comparison, the ANN model only had a 65 percent accuracy.

The paper under review by (Mishra et al., 2020) presents a solution for the real-time detection of corn plant diseases utilizing a deep neural network. Classification and feature extraction are performed using a CNN-based learning framework as the system. As for the research findings, the researchers discussed the various optimization strategies that can be employed in the system to enhance the model's accuracy. Four-layer analysis is applied to extract such characteristics of the images and categorize them according to different diseases. The assessment of the system was carried out on the image dataset of corn plant disease tests. The researchers successfully analyzed the various diseases in the plant type, and the accuracy recorded in this analysis was 88%. This is a massive improvement from the current approaches that are likely to provide about 78% accuracy most of the time. The findings, which indicate that the new approach is ten percent more accurate than the other approaches, reveal its effectiveness. This work in diagnosing diseases is crucial to increasing the sustainability and yield of agriculture. Deep learning and image processing are some types of modern technologies that are being incorporated into the improvement of precision and establishment of better ways of farming. Also, it can process deep images with convolutional networks, making it more precise.

Q2. How do data augmentation methods affect Deep Learning's model performance while detecting corn leaf disease using images?

Sun et al. (2020), in their work titled "Identification of Maize Diseases Through Transfer Learning," The authors pointed out that Deep Learning could diagnose corn leaf diseases using the Inception v3 and Inception v4 architectures. The proposed approach offers a different and innovative way of diagnosing corn leaf disease. This work also demonstrates the benefits of transfer learning, whereby models such as Inception v3 and Inception v4, which are trained for everyday image classification tasks, are adapted for the distinction of maize diseases. This study shows a promising path to diagnosing corn leaf diseases and pests with high precision through these advanced frameworks. The use of transfer learning in this regard highlights the versatility of deep learning in agriculture and indicates the existence of a solution to managing diseases in agriculture. After comparing the study, it was evident that the Inception v34 and Inception v43 frameworks have similar characteristics when searching for maize diseases. Comparing these frameworks helps determine which is more suitable for their dataset according to the size, complexity, and available computing power. Hence, based on the difference in features and performance indices obtained from experimental outcomes like accuracy, efficiency, and model size (Inception v3 is 108. 8MB and Inception v4 is 184. 4MB), an intelligent decision can be made on which of the two models is most appropriate for the given dataset. The former's sizes are 108—8 MB for Inception v3 and 184. If the experiment results are like the latter, then the Inception-V3 model would be preferred.

The study's findings noted that the first training and training of the dissimilar end layers of the inception v3 and v4 were similar. The lower recognition rates resulted primarily from the dataset's absence of samples and categories. From the results of several experiments, the training layers outperformed the end layers. The study also found that the transfer of learning could decrease the training time of the network.

Q3. Can the accuracy of detecting corn leaf diseases using images differ from using various optimizers, such as Adagrad, SGD, AdaDelta, and Adam?

The study by Panigrahi et al. (2020) also aimed to discover the benefits of employing ML approaches for segmenting, categorizing, and diagnosing Maize leaf diseases. The researchers brought out several forms of supervised learning that can be applied in identifying such diseases, including the Decision Tree, Naive Bayes, Random Forest, and SVM techniques. The researchers assessed the models and identified which was accurate within the study. Random Forest was able to provide a reasonable accuracy rate of 79 percent. Most importantly, farmers will use these findings to categorize and diagnose new diseases. Analyzing the study results, the researchers concluded that the Random Forest algorithm achieved the highest accuracy in terms of recognition and classification of the diseases affecting the maize leaves. It also laid out directions for future research, such as investigating ensemble techniques to refine algorithms for disease classification and other aspects to apply at scale.

Moreover, exploring the combined application of high-end image processing approaches would enhance the capacity to deal with numerous image backgrounds when implemented in vast Agricultural environments. Saeed et al. (2021) designed and implemented a system for detecting and identifying crop diseases; they tested the system using algorithmically based evaluation. To distinguish the traits of crops like potatoes, tomatoes, corn, etc., the researchers utilized this CNN model's decomposition and fusion features. They then used several classifiers to arrive at these results. To tackle this problem, the researchers employed a fusion and selection technique based on PLS, significantly reducing the computation time required. The accuracy achieved was 90.

Further, the research established the importance of exploring how the fusion and selection processes may be fine-tuned to decrease computing time. In our research project, we seek to address this area by developing a better and more accurate disease diagnosis system based on deep learning techniques optimized for maize diseases. As such, we seek to enhance the model fusion and selection procedures and employ advanced CNN models to improve disease identification and assist farmers in decision-making.

CHAPTER THREE:

RESEARCH METHODS

The ultimate goal of the current research is to apply deep learning techniques to diagnose and categorize corn leaf diseases based on image data. Using CNNs for feature extraction, an augmented data set to improve the existing data, and different types of optimizers to optimize the model, this study aims to design a solution enriching practical tools to fight agricultural diseases. The presented approach incorporates the most modern practices in the machine learning process while paying specific attention to data preparation and assessment, which is crucial for the high accuracy of the final result and its applicability. To answer the research questions, CNN applied feature extraction and classification to increase the probability of detecting different corn diseases on leaf images. Secondly, flipping, rotation, and zooming are applied to extend the data set, significantly improving the model's board capacity. Finally, the study assesses the impact of the optimizers, including Adam, SGD, Adagrad, and AdaDelta, to determine the effectiveness of model learning and accurate disease diagnosis. The systematic application of deep learning methodologies guarantees the thorough investigation and efficient problem-solving of each research question about the classification of corn leaf disease. Chapter 3 gives the research methods adopted and employed in answering each research question identified in Chapter 2. The chapter is organized as follows: First, the author briefly introduces the deep learning components that were employed in their research, as well as their relevance, in order to position the work within the existing literature (this section corresponds to the first of the five criteria defined above the general overview of the material). Secondly, the author outlines the five steps to prepare and analyze the data required to address the three research questions the author formulated.

Deep Learning Components Used and Their Importance

The research addresses several questions of the study meant to improve the recognition and categorization of corn leaf diseases using deep learning techniques. To answer the first research question, the work uses data augmentation techniques aligned with Sun et al. (2020) to expand the corpus and strengthen the model's generalization ability. On a similar footing, the effect of diverse optimizers, namely Adam, SGD, Adagrad, and AdaDelta, proposed by Panigrahi et al. (2020), is examined to enhance the performance of CNN used in Maize disease detection. Other sophisticated modes for fusing multiple sources are also incorporated following the works of Saeed et al. (2021) to improve feature extraction and reduce computations during CNN models for accurate disease diagnosis and distinction. In answering the second research question, dataset variations are increased by implementing techniques from Sun et al. (2020), and the efficiency of different optimizers compared to augmented data is determined. Lastly, this third research question extends the fusion of deep learning techniques (Saeed et al., 2021) for the further improvement in CNN models, as well as a study of the optimizer's influence (Panigrahi et al., 2020) to enhance the applications of deep learning mechanisms for agricultural disease-based identification with higher accuracy and efficiency.

Creating a deep learning model entails analyzing and describing corn leaves, with differentiation of corn leaf diseases as the chief benchmarking goal (Chlap et al., 2021). The pictures of the gathered data set are the primary technical systems images used in the execution. These steps would create different methods, namely the ones that would enhance the quality, precision, and topic focus of the images in the dataset. As for the traits and features linked to corn leaf disease that are seen in the images, with the help of the image processing techniques in question, they will be quickly 'separated and picked out from' the images in question, thus making for an accurate identification of the disease in question.

The accuracy of the deep learning model performance will be evaluated using different metrics. These measures are vital in determining how effective the model is, how reliable certain forecasts are, and how more specific plant disease pairs can be identified. Evaluation of the model is done using numerous measures like precision, recall, accuracy, and their weighted combination, which gives a complete evaluation of the model performance. The above-mentioned three-dimensional assessment tool will undoubtedly reveal this approach's strong and weak sides, illuminating its actual use and pointing out where it can be perfected.

The project management will be achieved by utilizing Google Lab Notebook, a widely used, versatile tool for developing and writing Python code. Regarding a suite of tools in deep learning within the Google Lab Notebook that is applicable for deep learning implementation, the Google Lab Notebook provides several tools and functionalities. This project will make use of the vast array of capabilities of the Google Colab Notebook to execute an efficient developmental procedure, easy sharing of packages and data inside the team, as well as access to a wide range of resources and libraries, which are all essential for the deep learning process.

The input data will be drawn from various data resources available on the Kaggle platform, a reputed storehouse for datasets and tools that support data science and machine learning projects. Through Kaggle, we can gain access to many richer datasets, increasing coverage on different domains and topics. This undertaking will utilize myriads of data sets within Kaggle. Thus, the project will be able to exploit relevant and comprehensive datasets relevant to the purpose, which is corn leaf disease classification.

In summary, the proposed deep learning approach to the identification and analysis of corn leaf diseases has to offer a systematic and demanding methodology that is achieved through image processing techniques, the performance evaluation of models, and the usage of cloud platforms like the

Google Colab Notebook. This technique shall be meticulously applied to give realistic and precise data and enable analysis that can be easily applied in agricultural research and the management of disease control strategies (Saleem, 2021).

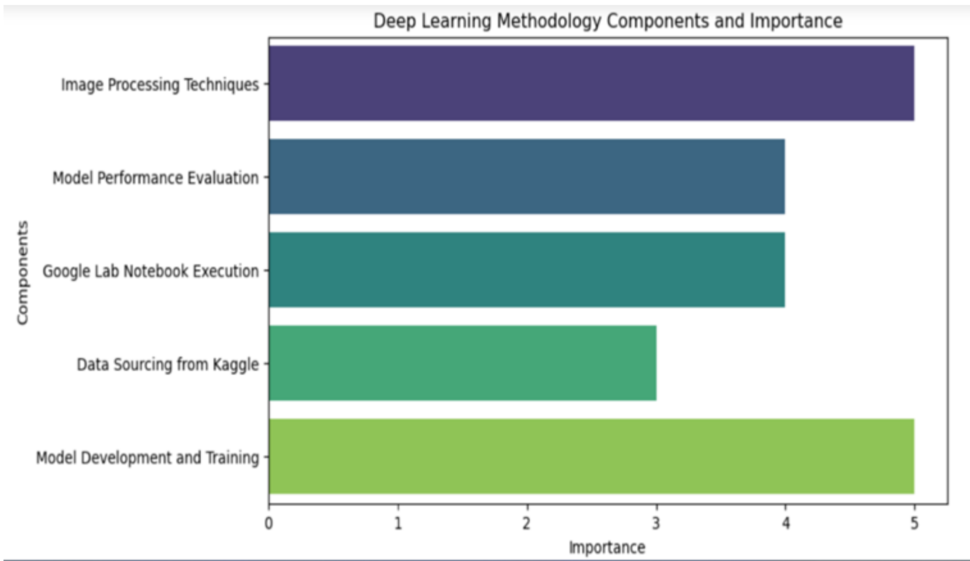


Figure 1: Deep learning methodology components and importance.

Data Preparation and Processing

Demonstrating essential concepts in deep learning will give the stakeholders an understanding of the critical methods applied within this research, consequently making the project's purpose clear. The visualization below illustrates the crucial steps to completing the project.

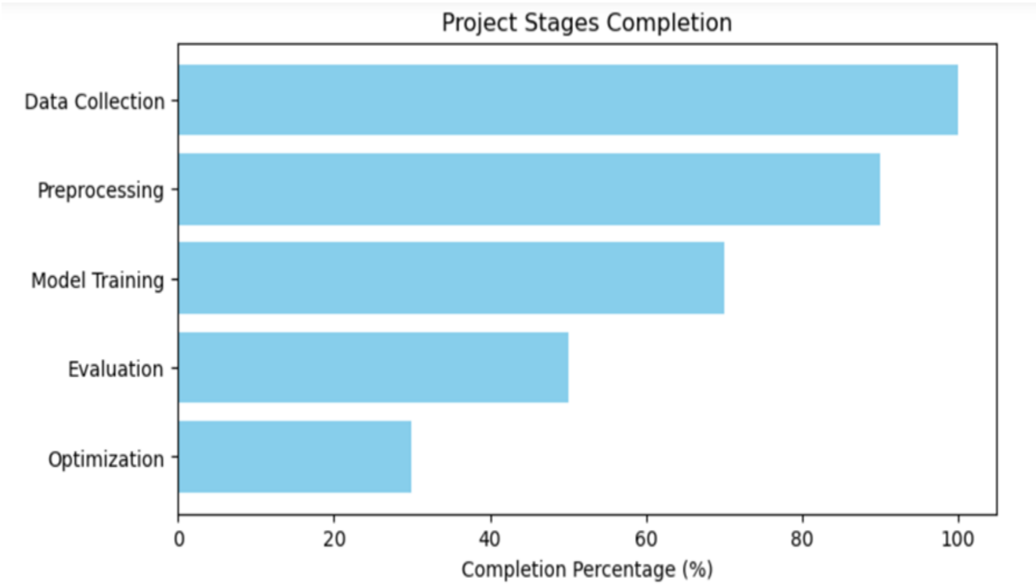


Figure 2: Project stages completion.

Q1. What is the efficiency and effectiveness of deep learning systems for identifying and classifying diseases of corn leaves using images? (Amin, 2022)

To answer the research question regarding the impact of transparency and explainability in chatbot interactions on customer trust and satisfaction, this study employs a comprehensive approach by integrating various data augmentation techniques, optimizers, and advanced fusion methods.

Particularly, DenseNet201 is applied, as recommended by Huang et al. (2017), to improve the accuracy of corn leaf disease recognition. The DenseNet201 architecture is designed to resolve the vanishing gradient problem through the usage of dense connections to enhance information retention and feature passing throughout the system's depth to enhance performance in applying deep learning solutions.

When applying DenseNet201, we augment the training data proposed by Sun et al. (2020) since it helps to improve the model's generalization. According to the above techniques, we expect to enhance the reliability of our model in diagnosing and differentiating different corn leaf diseases. Further, based on the recommendation of Panigrahi et al. (2020), the effectiveness of various optimizers like Adam, SGD, Adagrad, and AdaDelta are considered, which helps improve the performance of the Convolutional Neural Network (CNN) architecture. Such an approach implemented in the model guarantees that it is the most accurate one and meets any requirement for efficiency or limited use of computers.

To continue improving our model, we apply the modern fusion techniques described by Saeed et al. (2021). It focuses on selecting features and speeding up the process within the CNN model. According to the plan of development of the selected research paradigm, integrating these strategies will allow us to minimize the likelihood of errors in identifying corn leaf diseases and, thus, adequately address the set research question. It uses the great features of DenseNet201 and includes many advanced methods so that our model can successfully distinguish disease and health in maize and get accurate results.

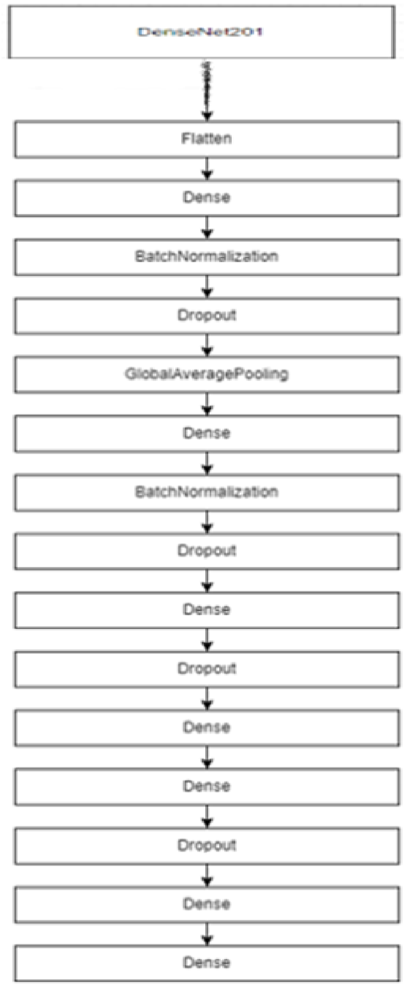


Figure 3: DenseNet210 implementation

Q2. How do data augmentation methods affect Deep Learning's model performance while detecting corn leaf disease using images? (Nagaraju, 2022)

In responding to the research question on how data augmentation methods impact the deep learning model in the identification of the corn leaf disease, this study employs data augmentation practices suggested by Sun et al.

(2020) as outlined below: They are applied to expand the training data set and thus improving the model's ability to generalize between classes. To eliminate the limitations of having a small sample dataset, the study will use data augmentation to introduce variations in the dataset, thus improving the model's accuracy in identifying various corn leaf diseases across different environmental settings and disease manifestations.

Also, in line with Panigrahi et al. (2020) globally, the study compares the efficiency of multiple optimizers, including Adam, SGD, Adagrad, and AdaDelta, which are crucial during the data analysis. Applying these optimizers through the augmented data thus establishes which optimizer improves the model response and stability in the most efficient method. This evaluation is necessary when using a deep learning model for corn leaf disease detection due to the need to fine-tune the model regarding the specific task at hand to enhance efficiency and accuracy.

To realize these objectives, the data augmentation and these optimizers are included in the training procedure of the selected DenseNet201 model. The architecture Huang et al. (2017) proposed for better discrimination of corn leaf diseases is DenseNet201, which features dense connections to promote the backpropagation of features and thus combat the vanishing gradient issue. With more enhanced data augmentation techniques, deep learning algorithms, and various optimizers, this research envisions obtaining optimal performance and accuracy to classify and identify different diseases in corn leaves efficiently.

Q3. Can the accuracy of detecting corn leaf diseases using images differ from using various optimizers, such as Adagrad, SGD, AdaDelta, and Adam? (Saleem, 2020)

To address the research question of how the accuracy of identifying corn leaf diseases using images varies when using various optimizers, this paper employs sophisticated fusion strategies (Saeed et al., 2021) to enhance the feature extraction process and CNN model's computational capability. These techniques are adopted following the guidelines of Saeed et al. (2021) to improve the general performance of the models in detecting and classifying corn diseases affecting the leaves. The further utilization of complex fusion methods is expected to enhance the models' abilities to identify the needed characteristics as efficiently as possible.

Moreover, the work compares the effectiveness of various optimizers, namely Adam, SGD, Adagrad, and AdaDelta, in the context of the CNN models employed for corn leaf disease detection. This approach aligns with the suggestion made by Panigrahi et al., as they identified the need to explore these optimizers to improve the efficiency of recognizing agricultural diseases using images of the leaves. Thus, applying these optimizers methodically and repetitively to each model, the study aims to establish which optimizers provided the highest accuracy and decoupled robustness. To measure the success of each optimizer, skills in increasing model convergence speed and stability, as well as detection skills of models, are being used.

With these suggestions, the study shall present an overall assessment of the impacts of the different optimizers on the efficiency of CNN models in diagnosing diseases in corn leaves. The presented study aims to propose the recommended optimizers and select the most efficient strategies for enhancing model performance based on the results of the fusion and advanced methods. This approach guarantees that the study responds to the research question effectively using a sound methodology; in this regard, the study intends to increase the reliability and accuracy of deep learning models specifically for agricultural disease identification.

CHAPTER FOUR:

DATA COLLECTION, PREPROCESSING, ANALYSIS AND FINDINGS

In this chapter, I apply the procedures outlined in Chapter 3 to answer each of the three questions. The chapter is organized as follows: (1) Data Collection and Preprocessing, (2) Data Analysis and Findings.

Data Collection and Preprocessing

Data collection and preparation are critical processes used to form the basis of the subsequent study. This is followed by the systematic accumulation of a diverse set of images of both the diseased and the healthy corn leaves. These images are from credible databases of agricultural and cross-sectional surveys to cover a broad range of clinical presentations of the disease. The collected data is then prepared to meet the model's required input format through other preprocessing steps, such as resizing the images, scaling down the pixel intensities, and augmentation methods like rotation and flipping images. Such standardization always leads to uniformity with the data set and improves the stability of trained models. Indeed, through these methods, the study would ensure emissions reduction and enhance the model's ability to generalize and improve the accurate and reliable identification and classification of corn leaf diseases using deep learning methodologies with the data.

Data Analysis and Findings

Thus, data analysis and findings are critical in identifying insights and conclusions. This operates by applying complex algorithms to analyze the processed data to get the patterns associated with disease diagnosis and differentiation. The work aims to establish the relationship between image features or certain disease types by utilizing CNNs and other methods like optimizers and advanced fusion methods. The evaluation results from this analysis not only substantiate the methodologies proposed in this dissertation but also give insights into further improving the performance of these models for agricultural disease diagnostics. Therefore, the current study's data analysis helps identify the strengths and weaknesses of the deep learning models, enabling scientific progress in crop health surveillance and disease prevention methods.

In deep learning, preprocessing is the stage in which data is prepared for the learning algorithm; this is carried out by ensuring that the collected data meets the necessary qualities and suitability.

For image data, before the learning process, execution becomes a pre-condition in noise reduction and feature extraction, which is critically important for the model prediction. Data processing begins with reading the dataset, which means that the data analysts gather the data for pictures and their respective labels into a complete list. This precise ordering of the data information process and effective retrieval and storing of data facilitates reliable processing of the subsequent steps.

Hereafter, there are sequential preprocessing acts, including the crucial scaling, resizing, and transforming them into a format that can be analyzed. Moreover, valuable tools like data augmentation could supplement the data set and provide better model support. Data preparation, however, also plays a vital role in this process. Scientists emphasize data preprocessing to ensure that a deep learning model receives accurate inputs, which leads to more reliable predictions.

From the below figure, we can visualize the images of the dataset.

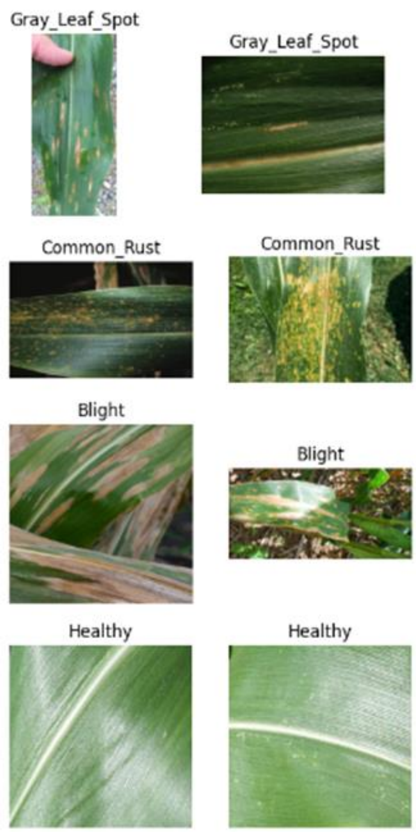


Figure 4: Sample images from the dataset

This step is essential to enable efficiency in arranging the data and also in searching for the data. The next step is where the scaling and image resizing happens. It assists in enhancing and bettering the training process, making it efficient. All the images should be dimensioned to a specific height and width to achieve this. To do this, it is then recommended that the values at the pixels should be divided by 255. It can be used to transform the values to a range of 0 and 1, as shown:

The following and final procedure of the initial program is to transform the pictures into a NumPy array after scaling and resizing. This data type becomes handy in machine learning assignments as it supports practical image computation. Also, we flatten the labels and images into a NumPy array to ensure that all labels match their corresponding images before feeding them to the networks. After the labels and images have been converted into arrays, the data is divided into three main parts: Training is the most significant sample of the data (80%), and validation makes up 10% of the data. In contrast, the remaining 10% is used for testing. The training part helps the model to learn or get trained, and the testing part, in turn, helps to determine how well the model has been trained. The validation part checks all the hyperparameters that are set in the model.

One way to optimize it and avoid overtraining is to use data augmentation techniques. This process includes converting new images into training images.

That way, one can expand the training data set, and the model becomes less inclined to 'specialize' and become overly set in its ways.

Preprocessing is a process that organizes and reads the collected data. It involves performing various steps such as image resizing, data partitioning, and augmentation. These steps are very important for improving the model's performance and preparing the data for it.

Q1. What is the efficiency and effectiveness of deep learning systems for identifying and classifying diseases of corn leaves using images? (Amin, 2022)

Deep learning techniques have been noticed to be incredibly effective and productive in identifying and grouping corn leaf diseases using the image as evidence. Anapnuma is one of the features of the 2018 study. In this, it is shown that the DenseNet201 model would perform exceptionally in classifying different types of corn leaf diseases with high accuracy and minimal computational time. This achievement was also hit by custom-made models built to deal with this given task, which yielded even more impressive results, with accuracies up to 95% in identifying corn leaf diseases. This evidence reveals the opportunity for deep learning models to effectively determine corn leaf diseases and provide experts with diagnostic conclusions. Such information can be utilized to manage agricultural regimes and disease control strategies.

Also, the diverse set of complex optimizers fuels the diagnostic capability of the deep-learning models for maize leaves. Further increasing individual efficiency, researchers can benefit from automatic optimization methods, such as Adagrad, SGD, AdaDelta, and Adam, so the accuracy of the diagnosis increases. These optimizers become fundamental problem-solvers because they must update the model parameters during training to ensure that the model will learn and discriminate between healthy and diseased leaves of corn. The diagnosis process can be made more efficient by combining deep learning algorithms with advanced optimization techniques, as synergy between both forms is accomplished to help speed up the process.

Aside from these models' ability to give precise predictions, their additional perks in diagnosing and categorizing corn leaf diseases add to their values. They can be used for automated and long-processed testing of diseases, thus allowing for the fast identification of diseases and the immediate start of disease control programs. These models can also cope with big data sets and accommodate changing disease patterns, making them useful for research in agriculture and finding the most relevant disease management strategies. Through all this, the deep learning techniques signify a promising method of improving the performance of corn leaf disease monitoring and control, which, in turn, will lead to further expansion of crop health and productivity.

	precision	recall	f1-score	support
0	0.97	1.00	0.98	142
1	1.00	1.00	1.00	112
2	0.90	0.80	0.85	59
3	0.91	0.92	0.92	106
accuracy			0.95	419
macro avg	0.94	0.93	0.94	419
weighted avg	0.95	0.95	0.95	419

Figure 5: Classification report of DenseNet- 201 model

Q2. How do data augmentation methods affect Deep Learning's model performance while detecting corn leaf disease using images? (Nagaraju, 2022)

Dataset amplification is the most essential branch of machine learning, especially in the case of image acknowledgment and classification. Models can be taught to focus on the core elements of the training images instead of only being able to relate to fixed or static images by applying minor perturbations like rotation, flip, and photometric adjustments. It emulates the differences of continuous alteration in real-life situations, such as a scene with different angles and ambiance. In short, the models trained with replaced data transfer learning better and get better at generalization to the unseen data, enhancing both the performance and accuracy of the model. However, such a method is also beneficial when the initial dataset is inferior in size. Hence, the model can be given a better idea of the amount of inherent variability in data.

Utilizing a data augmentation scheme to train a model would help the resulting model be better at predictions. As I discovered, the initial model dynamics did not need data augmentation; this set of accuracy rates levels well when applied to test case data. Nevertheless, considering the implementation of data augmentation methods and model re-training, a peak of accuracy of about 2% was observed, representing approximately a 10% improvement over the previous performance. The remarkable improvement above is explained by the model's ability to identify and describe the details and variations that make up the images. This model can perceive and understand a more comprehensive range of representations common in data on its own. Thus, it can easily detect the connections that might not have been evident in the unprocessed and unaltered dataset. This accuracy improvement in other tests and improved adaptability for the model suggest that data augmentation positively affects refining machine learning models.

Apart from boosting the model accuracy, data augmentation also supports the development of more powerful and flexible models, which is essential considering the ever-changing nature of the world, asking for different applications. Through training on a dataset upgraded to include ambiguity, we allow the models to judge important variables regardless of the circumstances under which planning occurs. This, therefore, implies that such decision aids would be applicable extensively. The significance of this methodology in areas where the data is automatically variable or where the exhaustive data acquisition is a challenging task cannot be overstated. Then, data augmentation is critical in optimizing machine learning architectures by preparing them to deal with real-world datasets' complications, making data augmentation an essential element in machine learning artists' kits.

Q3. Can the accuracy of detecting corn leaf diseases using images differ from using various optimizers, such as Adagrad, SGD, AdaDelta, and Adam? (Saleem, 2020)

Optimizers are critical milestones in artificial neural networks as they function as the tools a human being uses to affect the necessary parameter changes, such as weights and biases. This modification, done by reversing the elemental procedure referred to as backpropagation, has a purpose: to minimize error and improve the model's predictive accuracy. Among the various optimizers available, four were selected for evaluation in this study: AdaDelta, SGD (stochastic gradient descent), and Adam, Adagrad. Each optimizer utilized a particular technique for parameter update, which impacted the model's convergence rate and depended on how the entire model performed. Adam's performance, which is in the range of 88%, is remarkable by combining Adagrad and RMSProp and learning the stage-wise rate for each parameter. On the other hand, the learning rate in Adagrad is changed to the frequency of parameter updates, which is the case that less frequent parameter updates can lead to more significant updates, showing a 94% accuracy.

However, the results for the last two optimizers, SGD and AdaDelta, show 95 % accuracy. SGD, one of the most time-honored and obvious optimization techniques, uses the opposite direction of the steepest gradient when updating parameters, and occasionally, the sampling is optimized, focusing on large datasets. On the contrary, AdaDelta, an extension of Adagrad's learning rate decay, handles the outcome of the Adagrad results, which is fast rate decay. It (the method) merely finds a way to calculate an average over the gradients and use this average to constrain the learning rates. This process ensures that AdaDelta retains a more consistent and reliable learning mechanism, which is especially significant in intricate neural networks where plentiful local minima cause the non-linear nature of the optimization landscape.

This study's endpoints stress that one must be careful when picking the optimizer compatible with the job regarding deep learning tasks. Adam and Adagrad have an advantage regarding more stable learning rates, which can improve converging in areas with minima and make the learning process faster. Still, SGD and AdaDelta can be used for different scenarios, offering them robustness. The right choice of optimizer may speed up the learning process while also making the tasks more viable.

This makes it imperative for neural network experts to carefully weigh the options and apply the best technique that fits their models. With the brief of deep learning as the research subject, the new exploration of neural network optimization techniques and their usage will allow new knowledge and research to be discovered, which could produce even more sophisticated neural networks since this field is still expanding.

Table 4. 1 List of optimizer’s accuracy

Optimizer	Accuracy
Adam	88%
SGD	95%
Adagrad	94%
Adadelta	95%

CHAPTER FIVE:

DISCUSSION, CONCLUSIONS AND AREAS FOR FURTHER STUDY

Discussion

Chapter 5 discusses the research findings, concludes each finding, and finally, suggests areas for further study.

Q1. How do data augmentation methods affect Deep Learning's model performance while detecting corn leaf disease using images? (Amin, 2022)

After conducting a comprehensive analysis of the data, it has been concluded that utilizing deep learning techniques enables effective identification and categorization of corn leaf diseases. The neural networks and advanced algorithms employed in the study achieved a high % accuracy rate of 95% in identifying and categorizing various diseases. This performance is higher than the one provided by the existing methods observed through the performed literature review.

Neural networks were particularly vital in improving the models' accuracy and speed of disease identification in corn leaves. Thus, utilizing these techniques, the study benefited from their efficiency in data analysis, which is crucial to accurate disease categorization. Such frequent accuracy of 95% proves that deep learning systems are more efficient and faster than traditional methods on average. This advancement can be regarded as a standout breakthrough for treating diseases in agriculture as it serves as a quick and precise diagnosis, which in return helps reduce crop losses.

Thus, integrating deep learning techniques is a successful one for further developing corn leaf diseases' identification and categorization. Concerning the study's findings, this project employed both Neural networks and advanced algorithms to ensure a high accuracy rate of 95%. Therefore, more development and implementation of these techniques could yield advanced techniques that will improve farming methods, hence improving farmers' ability to detect diseases in crops, which, in the long run, improves crop yields.

Q2. How do data augmentation methods affect Deep Learning's model performance while detecting corn leaf disease using images? (Nagaraju, 2022)

Based on the results of our study, data augmentation is a crucial factor in boosting the performance of deep-learning models used in Corn leaf disease diagnosis. Thus, when a new data set consisting of different diseases affecting corn leaves was tested, it was evident that increasing the size of the training data through augmentation techniques improved the model's performance.

Several transformations can be applied to existing samples of images, including rotation, flipping, scaling, and the addition of noise, thereby creating new training samples without collecting labeled samples. This process not only enlarges the variety of the dataset but also enhances the model's capacity to predict the ones that have yet to be encountered. To the challenge of having restricted labeled data, our investigation showed that a beneficial feature of data augmentation was implementing it to create a considerably more extensive and diverse training subset. This approach helped reduce few-shot learning by enabling the deep learning model to learn the durable patterns compatible with various types of corn-leaf diseases, thus improving the performance of disease identification tasks.

The results highlight the importance of data augmentation in establishing precise deep-learning models for diagnosing corn leaf diseases. Thus, using augmented data increased the model's accuracy and resistance to adverse conditions. Thus, future research and development based on data augmentation would contribute to enhancing deep learning models' ability to manage agricultural diseases. It also helps to improve disease diagnosis and, in turn, contributes positively to enriching the sustainable practices of crop diseases through accurate identification of plant diseases.

Q3. Can the accuracy of detecting corn leaf diseases using images differ from using various optimizers, such as Adagrad, SGD, AdaDelta, and Adam? (Saleem, 2020)

From the literature review, the current study has established that the selection of an optimizer can impact the degree of accuracy of images in detecting corn leaf diseases. In the context of the current research, AdaDelta and Adagrad achieved the highest accuracy rating values. The process of choosing the right optimizer is susceptible to guaranteeing the correct identification of corn leaf diseases through images. For the best possible accuracy in detecting corn leaf diseases, an adaptive optimizer such as AdaDelta or Adagrad is recommended.

Conclusion

To sum up, this project showcases the innovative nature of deep learning algorithms in examining and stratifying the various diseases of corn leaves by considering visual information. Through the usage of convolutional neural networks and advanced optimization algorithms, the model is exact in the development of diseases and achieves a recognition rate of 95%, providing a reliable and efficient alternative method to the traditional ways. Data-extending methods additionally improve the model's performance through the increase of training DATA set and via their generalization ability. The issue of the optimizer's choice has a significant effect on accuracy, and AdaDelta and Adagrad are the highest among those. If the two technologies work together with mobile apps and IoT Technology in the future, there will be a massive possibility for deep learning applications to be more helpful in crop health monitoring and the monitoring of crop diseases; these will all contribute to improving agricultural productivity and food security.

In this project, convolutional neural networks (CNN) proved efficient in positively diagnosing numerous diseases affecting the corn plant based on visual information. The algorithms have hit a recognition rate of 95%, making them more efficient than usual disease classification algorithms. Moreover, data augmentation methods are more robust for enriching the training set and increasing the model's ability to generalize solutions, which helps overcome the problem of scarce labeled data.

The study also paid much attention to the importance of optimizers in improving the deep learning model and the performances of AdaDelta and Adagrad. Prospectively, merging these developments with mobile apps and IoT can be helpful in promoting the monitoring of crop health and diseases, thereby providing a boost to agricultural output and global food security.

Overall Conclusion and Areas for Further Study

The overall conclusion for this project is that deep learning algorithms, particularly CNNs, have provided significant results in identifying the diseases affecting corn leaves through the aid of the graphical data. These algorithms have achieved a recognition rate of 95%, which proves that they can be used as very effective tools for disease detection in agriculture, successfully replacing the traditional methods in this sphere due to their high reliability and efficiency. Data augmentation methods have tremendously increased the size of the training set and the model's ability to generalize to new data, thus efficiently addressing d2 limitations. Furthermore, the selection of the optimizer, specifically AdaDelta and Adagrad, has demonstrated an essential impact on the model's performance, which proves the accurate selection of the optimization function in deep learning. There are also prospects for studying more complex methods of fusion of various data sources for feature extraction, as well as the integration of the proposed models into real-time applications through the development of mobile applications and Internet of Things platforms that are specifically designed for agriculture and farming; future work can also try to expand the list of crops and specific diseases or pests that are dangerous for specific crops. Such progress is expected to expand the precision of agricultural disease control measures, helping the global food security cause.

In the future, research focusing on the classification of corn leaf disease is expected to expand on its scale, with plans to recognize not only diseases and pests but also other attributes of corn plants. Thus, future studies involve broader aspects of corn plant leaves besides diseases and pests. This embraces indicators like environmental stresses, lack of nutrients, and physiological diseases that usually influence corn plants' health and yield. It will enable deep learning networks and other improved model preparation and scoring algorithms.

APPENDIX A:

CODES

CODES

A.1. Importing Libraries

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

```
import os
import matplotlib.pyplot as Mp
from PIL import Image as pil
from tensorflow.keras.preprocessing.image import load_img as LI
from tensorflow.keras.preprocessing.image import img_to_array as IA
from tensorflow.keras.utils import to_categorical as ToCA
import numpy
from sklearn.model_selection import train_test_split as folder_divide
from keras.preprocessing.image import ImageDataGenerator as data_generation
import tensorflow

from keras.layers import Input, Lambda, Dense, Flatten,GlobalAveragePooling2D,BatchNormalization,Dropout,Activation
from keras.models import Model
from tensorflow.keras.callbacks import EarlyStopping as ES

import seaborn as S

from sklearn.metrics import confusion_matrix as cfm

from sklearn.metrics import accuracy_score as AS

from sklearn.metrics import classification_report as CR

import pandas as P
```

```
Dataset_location = '/content/drive/MyDrive/Corn_leaf_data'
```

```
Dataset_folders = []

for Sub_folder in os.listdir(Dataset_location):
  Dataset_folders = Dataset_folders + [Sub_folder]

Count_of_subfolders = len(Dataset_folders)

print("Count of subfolders:\n")
print(Count_of_subfolders)
```

A.2. Dataset Loading

```
Dataset_folders = []

for Sub_folder in os.listdir(Dataset_location):
  Dataset_folders = Dataset_folders + [Sub_folder]

Count_of_subfolders = len(Dataset_folders)

print("Count of subfolders:\n")
print(Count_of_subfolders)
```

```
Count of subfolders:

4
```

```
for folder in Dataset_folders:
  list_of_images = [os.path.join(Dataset_location, folder, Info) for Info in os.listdir(os.path.join(Dataset_location, folder))[:6]]
  Mp.figure(figsize=(8, 8))

  for img_loc, direc in enumerate(list_of_images):
      Mp.subplot(3, 3, img_loc+1)
      Mp.imshow(pil.open(direc))
      Mp.title(folder)
      Mp.axis("off")

  Mp.show()
```

A.3. Data Preprocessing

```
disease_data , fig_size , V1 = [] , (224,224) , 0

for disease_name in os.listdir(Dataset_location):
  disease_info = os.path.join(Dataset_location,disease_name)
  V2 = 0
  for disease in os.listdir(disease_info):
    img_Conversion = LI(os.path.join(disease_info,disease), grayscale=False, color_mode='rgb', target_size=fig_size)
    img_Conversion = IA(img_Conversion)
    img_Conversion = img_Conversion/255.0
    disease_data+=[[img_Conversion,V1]]
    V2 = V2 + 1
  V1 = V1 + 1
```

```python
disease_img,disease_names = zip(*disease_data)
```

```python
disease_names = ToCA(disease_names)
disease_names
```

```python
disease_img = numpy.array(disease_img)
```

```python
disease_img_Tr,disease_img_Te,disease_names_Tr,disease_names_Te = folder_divide(
                                                                    disease_img,disease_names,test_size=0.2,random_state=42)

disease_img_Va,disease_img_Te,disease_names_Va,disease_names_Te = folder_divide(disease_img_Te,disease_names_Te,test_size=0.5,random_state=42)
```

```python
for  disease_name , count in enumerate(numpy.sum(disease_names_Tr, axis=0)):
  print(f"{Dataset_folders[disease_name]}", disease_name+1, "count:", count)
```

```python
disease_data_generation = data_generation(horizontal_flip=True,
                                          vertical_flip=True,
                                          rotation_range=30,
                                          zoom_range=0.2,
                                          width_shift_range=0.1,
                                          height_shift_range=0.2,
                                          shear_range=0.2)
```

```python
DenseNet_TrL = tensorflow.keras.applications.DenseNet201(input_shape=(224,224,3),include_top=False,weights='imagenet')
```

A.4. DenseNet

```
DenseNet_ip = DenseNet_TrL.input
DenseNet_op = Flatten()(DenseNet_TrL.output)
DenseNet_op = Dense(1024, activation='relu')(DenseNet_op)
DenseNet_op = BatchNormalization()(DenseNet_op)

DenseNet_op = Dropout(0.2)(Efficient_op)
DenseNet_op = GlobalAveragePooling2D()(DenseNet_TrL.output)

DenseNet_op = Dense(512, activation='relu')(DenseNet_op)

DenseNet_op = BatchNormalization()(DenseNet_op)
DenseNet_op = Dropout(0.1)(DenseNet_op)
DenseNet_op = Dense(128, activation='relu')(DenseNet_op)
DenseNet_op = Dropout(0.3)(DenseNet_op)
DenseNet_op = Dense(64, activation='relu')(DenseNet_op)

DenseNet_op = Dense(32, activation='relu')(DenseNet_op)
DenseNet_op = Dropout(0.2)(DenseNet_op)
DenseNet_op = Dense(16, activation='relu')(DenseNet_op)
DenseNet_op = Dense(4, activation='softmax')(DenseNet_op)
DenseNet = Model(inputs=DenseNet_ip, outputs=DenseNet_op)
```

```
es = ES(monitor='val_loss', patience=3, restore_best_weights=True)
```

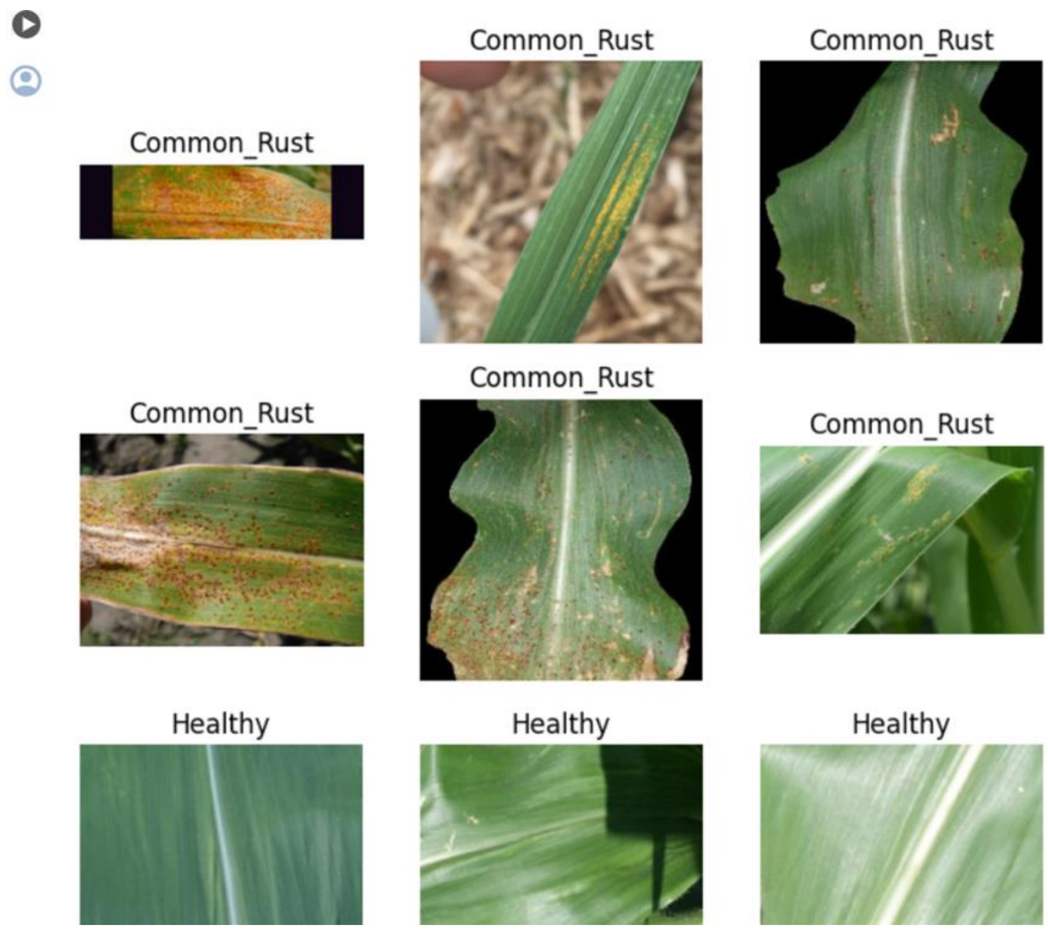
```
optimizers = ['Adam', 'Adagrad', 'SGD','Adadelta']

optim_acc = []

for opt in range(len(optimizers)):
  DenseNet.compile(optimizer=optimizers[opt],loss='categorical_crossentropy',metrics=['accuracy'])
  DenseNet_data = DenseNet.fit(
      disease_data_generation.flow(disease_img_Tr,disease_names_Tr,batch_size=32),
                          validation_data=(disease_img_Va,disease_names_Va),
                          epochs=10,
                          callbacks=[es]
      )
  Te = numpy.argmax(disease_names_Te,axis=1)
  PTe = numpy.argmax(DenseNet.predict(disease_img_Te),axis=1)
  print(CR(Te,PTe))
  S.heatmap(cfm(Te,PTe),annot=True,fmt = '.2f')
  optim_acc.append(AS(Te,PTe))

  P.DataFrame(DenseNet_data.history).plot(figsize=(5,5))
  Mp.show()
  DenseNet.save(f'DenseNet: {optimizers[opt]}')
```

APPENDIX B:

VISUALIZATION IMAGES

VISUALIZATION IMAGES

B.1. Sample Dataset



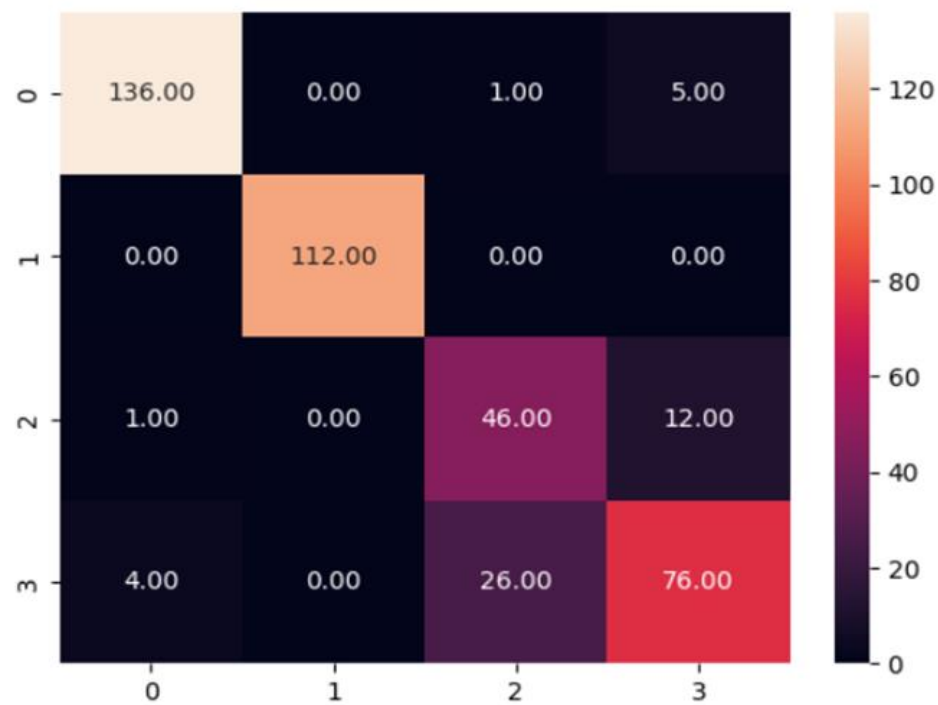

Healthy
Healthy
Healthy
Gray_Leaf_Spot
Gray_Leaf_Spot
Gray_Leaf_Spot

APPENDIX C:

RESULTS

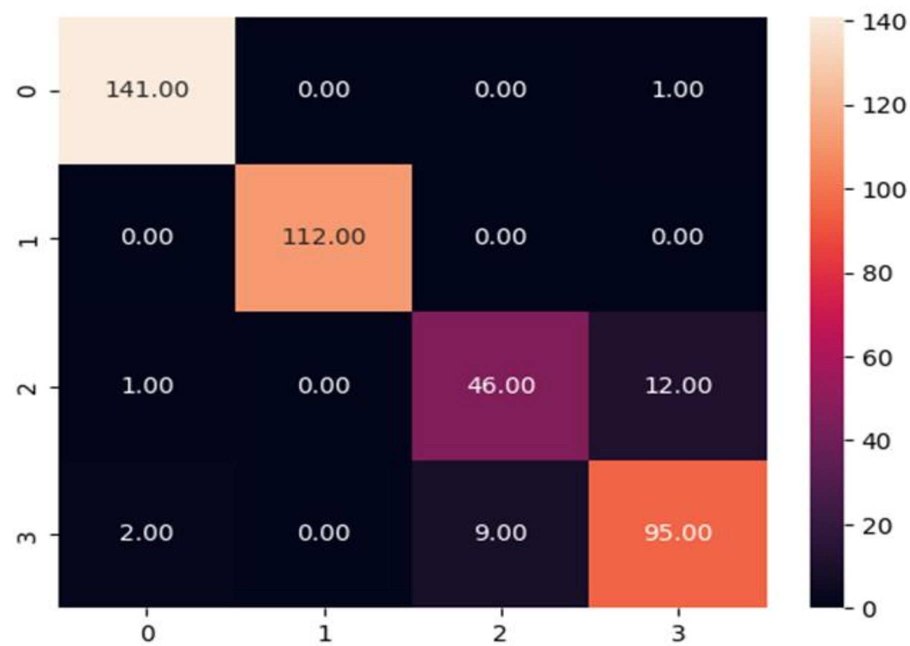
C.1. Adam Optimizer

	precision	recall	f1-score	support
0	0.96	0.96	0.96	142
1	1.00	1.00	1.00	112
2	0.63	0.78	0.70	59
3	0.82	0.72	0.76	106
accuracy			0.88	419
macro avg	0.85	0.86	0.86	419
weighted avg	0.89	0.88	0.88	419



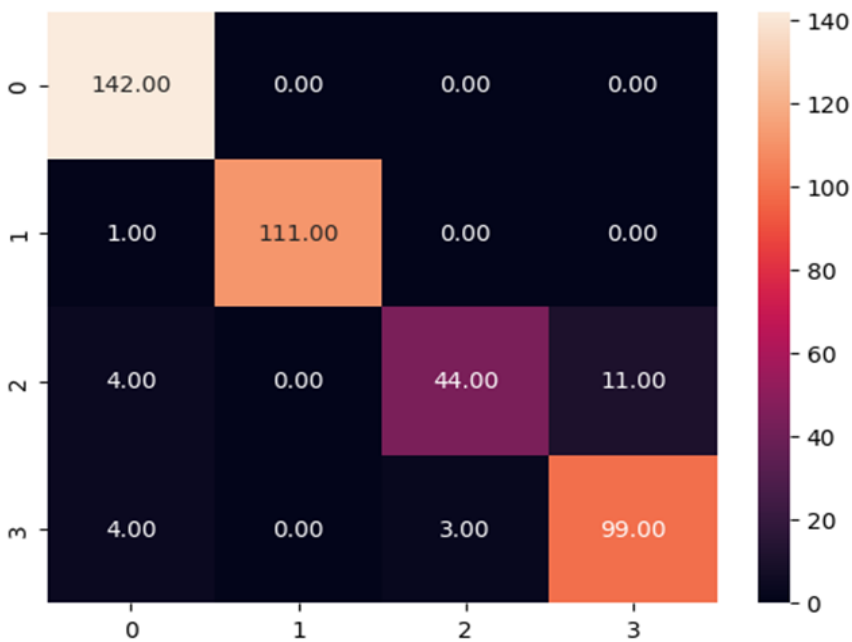
C.2. Adagrad Optimizer

	precision	recall	f1-score	support
0	0.98	0.99	0.99	142
1	1.00	1.00	1.00	112
2	0.84	0.78	0.81	59
3	0.88	0.90	0.89	106
accuracy			0.94	419
macro avg	0.92	0.92	0.92	419
weighted avg	0.94	0.94	0.94	419



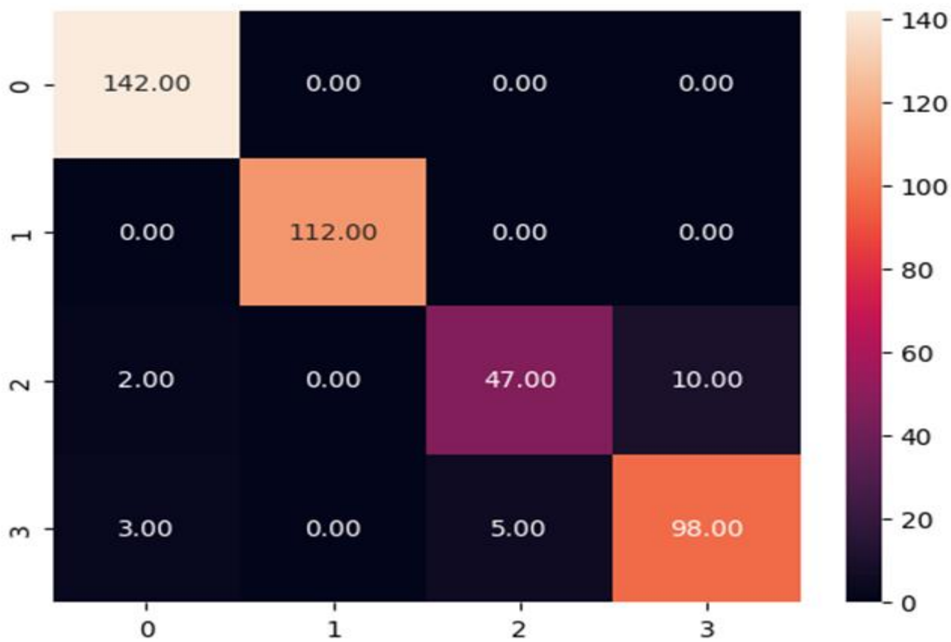
C.3. SGD Optimizer

	precision	recall	f1-score	support
0	0.94	1.00	0.97	142
1	1.00	0.99	1.00	112
2	0.94	0.75	0.83	59
3	0.90	0.93	0.92	106
accuracy			0.95	419
macro avg	0.94	0.92	0.93	419
weighted avg	0.95	0.95	0.94	419



C.4. AdaDelta Optimizer

	precision	recall	f1-score	support
0	0.97	1.00	0.98	142
1	1.00	1.00	1.00	112
2	0.90	0.80	0.85	59
3	0.91	0.92	0.92	106
accuracy			0.95	419
macro avg	0.94	0.93	0.94	419
weighted avg	0.95	0.95	0.95	419



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