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Deep Learning for Agriculture: Sweet Corn Disease Detection with Convolutional Neural Networks

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ABSTRACT

Sweet corn crops have a significant detrimental impact on agricultural productivity and food security because of their high vulnerability to several diseases. A timely and accurate illness diagnosis is essential for both disease treatment and yield enhancement. This paper suggests an automated method for classifying and identifying sweet corn diseases from leaf pictures that is based on convolutional neural networks (CNNs). The collection, which is separated into three categories—common rust, northern corn leaf blight, and maize dwarf mosaic virus—includes images of both healthy and damaged sweet corn leaves. Preprocessing techniques including scaling, normalization, and augmentation are applied to the images in order to increase the model's durability. The CNN design uses many convolutional layers, batch normalization, and dropout to maximize feature extraction and reduce overfitting. The categorical cross-entropy loss function and the Adam optimizer are used to train the model in order to achieve high classification accuracy. Performance is evaluated using precision, recall, F1-score, and confusion matrix analysis. Experimental results show that the proposed CNN model outperforms both pre-trained architectures and traditional machine learning methods in the classification of sweet corn illnesses. By facilitating proactive crop management and real-time disease identification, this work represents a major step toward incorporating AI-driven solutions in smart agriculture. Future studies will concentrate on developing a mobile application for field deployment in the actual world, adding attention methods, and growing the dataset.

Keywords: Sweet corn, convolutional neural networks (CNNs), Common rust, Northern Corn leaf blight, Maize dwarf mosaic.

I. INTRODUCTION

Zea mays var. saccharata, often known as sweet corn, is a widely grown cereal crop valued for both its economic importance and its exceptional nutritional content. However, a number of plant illnesses brought on by bacterial, viral, and fungal pathogens commonly threaten its output. Farmers suffer large financial losses as a result of these diseases' severe effects on crop quality, yield, and market value. For prompt intervention and efficient management, early and precise diagnosis of plant diseases is essential. Agricultural specialists conducting manual inspections, which are usually time-consuming, labor-intensive, and prone to human error, have historically been the mainstay of disease detection. Furthermore, physical examination is not feasible due to the enormous number of plants that require monitoring in large-scale farming. To overcome these challenges, a scalable, automated, and accurate way of recognizing sweet corn illnesses is offered via deep learning and computer vision techniques. [5]

Applications for image-based classification, such the identification of plant diseases, have been transformed by recent developments in deep learning, especially Convolutional Neural Networks (CNNs). The requirement for manual feature extraction is eliminated by CNNs' ability to automatically extract pertinent characteristics from images. This enables them to accurately identify good and damaged crops and spot intricate patterns in images of plant leaves. CNNs directly extract multi-level features from raw images, including color changes, texture differences, and disease-specific patterns, in contrast to conventional machine learning methods that rely on artificial features. CNNs have surpassed traditional classifiers in the identification of plant diseases due to their capacity to learn hierarchical representations.[10]

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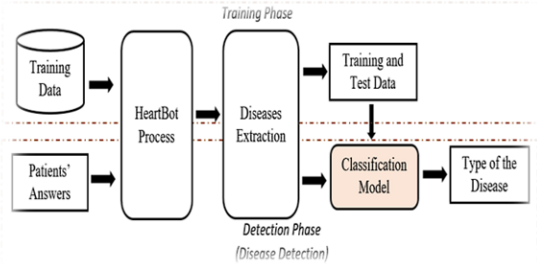

Figure 1: Workflow of Sweet corn disease Detection using CNN

Northern Maize Leaf Blight (Exserohilum turcicum), Common Rust (Puccinia sorghi), and Maize Dwarf Mosaic Virus (MDMV) are the most prevalent diseases that impact sweet maize. Common rust damages plants and decreases photosynthesis; it is characterized by orange-brown pustules on leaves. Northern Corn Leaf Blight is characterized by long, cigar-shaped, gray lesions that hinder plant growth and make the crop susceptible to other diseases. MDMV causes leaf bending, mosaic-like discoloration, and delayed development, all of which significantly reduce crop quality and output. Early identification is essential to effectively treat these illnesses and prevent their spread. Even though early detection is necessary, conventional sickness testing procedures have a number of drawbacks. First of all, visual inspection is inefficient and time-consuming, especially for large farms where it may be difficult to spot early signs of sickness. Second, diagnosing problems by hand is expensive and necessitates specialized knowledge that is frequently unavailable in isolated farming areas. Lastly, because various specialists may have differing opinions on symptoms, subjectivity in assessment could lead to contradicting results. An automated, AI-driven method that offers reliable and accurate disease identification is desperately needed in light of these difficulties. [14]

Figure 2: Example for Healthy, Infected and Spot Detected in the sweet corn leaves

With a focus on several important goals, this paper suggests a deep learning-based system for categorizing sweet corn diseases using CNNs in order to address these issues. To enhance model generalization and provide a varied depiction of different disease states, a comprehensive library of photos of sweet corn leaves is first created. To boost variability and avoid overfitting, high-quality photos are gathered and preprocessed using augmentation techniques. A CNN-based classification model is then put into practice with the aim of correctly distinguishing between various sweet corn illnesses and automatically extracting pertinent information from images. Deep feature learning is used to train and optimize the model for accurate categorization. Key performance measures include ROC curve analysis, F1-score, accuracy, precision, recall, and confusion matrix offer a comprehensive assessment of the system's resilience and performance. The proposed CNN-based method is also compared with other traditional machine learning techniques such as Support Vector Machines (SVM) and Random Forest classifiers to show its superior classification efficiency and accuracy. The project aims to achieve these objectives in order to create a highly accurate and scalable disease detection system that will significantly improve precision and smart farming applications.[18]

Our goal in this work is to use deep learning to create an automated illness classification system for sweet corn that will enable real-time, high-accuracy detection and do away with the need for manual diagnosis. Imagine a situation where a farmer discovers abnormal lesions and discoloration on the leaves of sweet corn. In the past, the farmer would have to manually examine the plants, seek advice from an agricultural specialist, and sometimes wait for the results of laboratory tests—a process that is expensive and time-consuming. Furthermore, misdiagnosis or a delay in action can cause the disease to progress and result in significant yield losses. We provide a CNN-based classification algorithm that can precisely identify illnesses in sweet corn leaf photos in order to overcome these difficulties. Creating a high-quality dataset including images of both healthy and sick leaves is the first stage. After that, the photos undergo preprocessing to enhance contrast, remove noise, and utilize augmentation methods like rotation and flipping to fortify the model. [24]

The CNN model is trained to automatically extract information like color variations, lesion patterns, and texture differences in order to reliably identify a variety of ailments, including Common Rust, Northern Corn Leaf Blight, and Maize Dwarf Mosaic Virus. The model can classify new photos once it has been trained to identify the type of leaf and determine whether it is healthy or diseased. The application also provides visual heatmaps that show impacted places and confidence scores to guarantee classification transparency. We assess the model's performance using important measures including accuracy, precision, recall, F1-score, confusion matrix, and ROC curves to make sure it is reliable and strong. Additionally, we illustrate the benefit of deep learning in plant disease classification by contrasting our CNN-based method with more conventional machine learning approaches like Support Vector Machines (SVM) and Decision Trees. In the end, our research establishes the groundwork for an AI-powered real-time diagnostic tool that may be included in intelligent agricultural systems. Using the model as a web-based or mobile application, farmers can simply snap a photo of a sweet corn leaf, upload it, and receive an instant diagnosis of the disease and treatment recommendations. For farmers worldwide, this strategy increases the efficacy, affordability, and accessibility of disease management by promoting precision agriculture, reducing crop losses, and facilitating early detection.[21]

2. LITERATURE REVIEW

Computer vision technology has developed at a never-before-seen pace over the last 10 years and is currently employed in a wide range of other industries, including agriculture. Artificial intelligence and computer vision have greatly enhanced agricultural operations, especially in the areas of early disease detection and crop health monitoring. Reducing losses, improving agricultural produce efficiency, and guaranteeing sustainable farming methods all depend on early disease identification. Convolutional neural networks (CNNs), which perform better than conventional machine learning methods, have transformed image-based analysis in recent years. One of CNNs' primary advantages is their ability to automatically extract significant features, which is essential for image recognition and categorization. Unlike conventional techniques that depend on manually produced features like color, texture, and morphology, CNNs automatically recognize the most relevant patterns in an image, improving classification accuracy.

Numerous CNN patterns have been created and are frequently used for the classification of plant diseases due to their efficacy. Among the popular architectures are DenseNet (Huang et al., 2017), ResNet (He et al., 2016), GoogLeNet (Szegedy et al., 2015), AlexNet (Krizhevsky et al., 2012), and VGG16 and VGG19 (Simonyan and Zisserman, 2014). These structures have been widely used in plant disease diagnosis because of their exceptional performance in image-based tasks and high classification accuracy levels for both healthy and diseased leaves. Strong deep learning models that can handle actual agricultural problems have been made possible by the growing quantity of labeled plant disease datasets and ongoing developments in CNNs.[28]

The diagnosis and classification of corn leaf diseases using machine learning and image processing techniques has been the subject of numerous studies. Alehegn (2020) classified maize leaf diseases using a technique based on digital image analysis. In order to classify the data using machine learning approaches, the study focused on identifying morphological, color, and texture properties in photos of maize leaves. Eight hundred images were collected and categorized into four groups: common rust, leaf blight, leaf spot, and healthy leaves. Twenty-two features were taken from each of the 200 images in each category in order to classify them. K-Nearest Neighbors (KNN) and Artificial Neural Networks (ANN) were the two machine learning models applied to this dataset. The results demonstrated that ANN outperformed KNN with an impressive classification accuracy of 94.4%, highlighting the benefits of deep learning over more traditional machine learning approaches.

Mohanty et al. (2016) conducted another noteworthy investigation with a publicly accessible dataset of 54,306 photos of both healthy and sick plant leaves. To categorize 26 plant diseases and 14 crop types, the researchers used a deep CNN network. They used both training from scratch and transfer learning strategies in their research using the CNN architectures AlexNet and GoogLeNet. CNNs may generalize across a variety of plant species and disease types, as demonstrated by the final model's remarkable accuracy of 99.35% on a held-out test set. This study was revolutionary because it showed how deep learning may outperform conventional techniques in the classification of plant diseases based on a sizable dataset. Arora et al. (2020) used an ensemble-based decision tree model called Deep Forest to classify maize leaf disease in a novel method. More traditional machine learning classifiers such as Support Vector Machines (SVM), Random Forest, Logistic Regression, and KNN were contrasted with Deep Forest in the study. There were 100 photos in each of the four categories that made up the dataset used in the study. With an accuracy of

96.26%, the final Deep Forest model, which included 1,000 trees, four forests, and three grains, outperformed the baseline machine learning models after hyperparameter adjustments.

Researchers have looked into object detection algorithms for disease identification in addition to more conventional classification methods. The study by Liu and Wang (2020), which created an enhanced YOLOv3 algorithm for identifying tomato illnesses and insect pests, is one noteworthy example. By adding multi-scale feature detection, bounding box clustering, and multi-scale training, the researchers improved YOLOv3. The dataset included 146,912 bounding boxes identifying afflicted areas and 15,000 pictures depicting 12 distinct tomato diseases. With a mean Average Precision (mAP) of 92.39%, the suggested YOLOv3 model performed better than earlier object detection models like Single Shot Detector (SSD) and Faster R-CNN. This development showed how well improved object identification methods can identify plant diseases, especially in intricate agricultural settings.

In a similar vein, Fuentes et al. (2017) suggested a deep learning-based detector for real-time tomato disease and pest detection. Three distinct object detection architectures were assessed in their study: Single Shot Multibox Detector (SSD), Region-based Fully Convolutional Network (R-FCN), and Faster R-CNN. Deep feature extractors such as VGGNet and Residual Networks (ResNet) were used in conjunction with each of these detectors. The dataset employed in this work contained a number of difficult conditions, including backdrop complexity, small item sizes, and fluctuations in illumination. According to the results, a plain CNN architecture outperformed R-FCN with ResNet-50, attaining a mAP of 85.98%, even though deeper networks did better overall. This study made clear how crucial it is to strike a balance between network complexity and depth when developing plant disease detection models for real-time applications.

Notwithstanding the impressive advancements in the classification of plant diseases, a number of obstacles still stand in the way of the useful use of these models in actual situations. Because plant illnesses frequently manifest differently depending on environmental factors, plant growth phases, and genetic changes, one of the main issues is the variety in disease symptoms. Model performance can also be greatly impacted by occlusions and differences in image quality brought on by dim illumination, shadows, and similar backdrop textures. The localization of diseases in the image is another significant problem because some diseases only show up in small, localized areas, which makes it challenging to detect them with conventional CNN designs. Moreover, acquiring large-scale labeled datasets for every potential plant disease is still difficult, and many plant species and diseases necessitate comprehensive domain-specific datasets.

We propose a deep learning-based method for classifying sweet corn diseases that uses CNNs to provide scalable, real-time, and extremely accurate disease diagnosis in order to get around these limitations. By incorporating attention processes, improving CNN topologies, and utilizing advanced data augmentation approaches, we aim to address the present difficulties in plant disease categorization. Additionally, to highlight affected areas and enhance end-user interpretability, our proposed model will make use of explainability strategies, such as Grad-CAM heatmaps. By building on earlier research and addressing existing limitations, this project aims to develop a practical, AI-driven system for automated sweet corn disease identification, assisting farmers and promoting precision agriculture.

3. CLASSIFICATION OF DISEASES

Sweet corn, like many other crops, is highly susceptible to a variety of diseases that can significantly impact yield and quality. These diseases, which affect plants at different stages of growth, are mostly caused by bacterial, viral, and fungal infections. Conventional disease detection techniques depend on expert evaluation and visual inspection, which are labor-intensive, time-consuming, and prone to human error. As deep learning and artificial intelligence have advanced, Convolutional Neural Networks (CNNs) have emerged as a reliable and efficient technique for automated disease classification. Because CNNs can extract fine-grained data like texture, color changes, and lesion patterns—all of which are essential for successful classification—they have shown great efficacy in image-based plant disease identification. This study uses a CNN-based method to categorize three important sweet corn diseases: Gray Leaf Spot, Northern Leaf Blight, and Common Rust.[8]

3.1 Common Rust: Puccinia sorghi produces common rust, a damaging fungal disease that damages sweet corn. The appearance of tiny, reddish-brown pustules on the upper and undersides of the leaf helps identify it. As the spores proliferate, these pustules gradually turn black, and if treatment is not received, severe necrosis will result. In warm, humid weather, usually between 15 and 25 degrees Celsius, the disease spreads quickly. Common rust hinders the plant's ability to perform photosynthesis, which results in early leaf senescence and reduced grain filling. It is difficult to correctly diagnose using conventional techniques since its symptoms visually resemble those of other fungal infections. Consequently, by identifying complex patterns from hundreds of annotated photos, deep learning models are essential for differentiating Common Rust from other foliar diseases. CNNs are trained on high-resolution pictures, which enables the model to accurately classify and detect pustules in their early stages by capturing the fluctuations in pustule size, color, and distribution.[5]

Figure 3: Common Rust Infected Leaves

3.2 Northern Leaf Blight (NLB): Another serious fungal disease that impacts sweet corn production globally is Northern Leaf Blight (NLB), which is brought on by Exserohilum turcicum. Long, oval, gray-green lesions that look wet at first but turn brown as the infection progresses are the disease's defining feature. These lesions could cover a significant area of the leaf surface and spread quickly. Typically, they follow the leaf veins. The disease is spread by airborne conidia and grows best in cold, humid regions, especially those with temperatures between 18 and 27°C. The ability of the leaf to photosynthesize is compromised as the lesions grow, which eventually lowers plant vigor and kernel development. One of the biggest challenges in detecting Northern Leaf Blight is the variance in lesion size and shape caused by different hybrid sweet corn cultivars and environmental conditions. Conventional machine learning algorithms struggle to deal with such shifts, even though CNNs may generalize across multiple datasets by identifying significant features unique to NLB. By employing convolutional layers to differentiate between lesion patterns resulting from NLB and other similar illnesses, the model guarantees high classification accuracy.[9]

Figure 4: Northern Leaf Blight Example

3.3 Gray Leaf Spot (GLS): Another serious foliar disease that is a serious threat to the production of sweet corn is Gray Leaf Spot (GLS), which is brought on by Cercospora zeae-maydis. Small, whitish lesions that progressively enlarge into long, rectangular patches with distinct borders are its defining feature. Under extreme infections, these lesions frequently combine to create sizable necrotic patches that result in widespread leaf blight. The disease is especially aggressive when leaves stay moist for long periods of time and spreads quickly in warm, humid conditions. In contrast to other illnesses, Gray Leaf Spot is distinguished by the shape of its lesions and, in its early stages, by the yellow halo that surrounds the afflicted areas. However, it could be challenging to correctly diagnose using conventional image-processing techniques because lesion color and texture can vary depending on the lighting. By identifying intricate spatial hierarchies in the images, CNNs get around this restriction and successfully differentiate GLS lesions from other fungal diseases. CNN-based algorithms are a dependable method for real-time disease surveillance because they can precisely split and categorize contaminated areas by analyzing high-dimensional data.[9]

Figure 5: Gray Leaf Spotting in Corn

Like many other crops, sweet corn is extremely vulnerable to a variety of bacterial, viral, and fungal diseases that have a major effect on both its output and quality. Common Rust, Southern Corn Leaf Blight (SCLB), Northern Corn Leaf Blight (NCLB), and Gray Leaf Spot (GLS) are some of the most common and economically detrimental diseases. In addition to affecting leaf health and lowering photosynthetic efficiency, each of these diseases has distinct visual signs that, if ignored, can result in significant yield losses. For efficient disease control and crop protection, these diseases must be accurately and promptly identified. However, because different illnesses have overlapping visual characteristics, traditional diagnostic approaches can be time-consuming, error-prone, and frequently require expert expertise.[16]

In order to overcome these obstacles, Convolutional Neural Networks (CNNs) and deep learning-based classification offer a potent and effective method for automated disease identification. CNN models are able to precisely distinguish between various disease types by extracting complex information including lesion shape, texture, and color patterns. The suggested approach seeks to improve the precision and dependability of disease diagnosis by training on a varied dataset that includes high-quality photos of both healthy and diseased sweet corn leaves. In addition to helping farmers and agronomists make well-informed decisions, this also supports early intervention tactics, which lessen the severity and spread of illnesses. An important step toward sustainable farming is the use of AI-driven methods for agricultural disease classification, which will increase productivity and lessen reliance on chemical treatments.

Disease Name	Causal Agent	Symptoms	Favorable Conditions	Yield Impact
Common Rust	*Puccinia sorghi*	Reddish-brown pustules, leaf necrosis	Humid, 15-25°C	High
Northern Leaf Blight	*Exserohilum turcicum*	Large, tan-colored lesions along veins	Cool, wet, 18-27°C	Severe
Gray Leaf Spot	*Cercospora zeae-maydis*	Grayish, rectangular lesions with sharp edges	Warm, humid, prolonged leaf wetness	Moderate to severe

Figure 6: Overview of Diseases

4. TRADITIONAL METHODS

Historically, manual inspection and early computer methods have been used to identify and categorize sweet corn illnesses. One of the most popular techniques is manual expert diagnosis, in which agricultural experts visually inspect crop leaves for signs like lesions, discolouration, wilting, and irregular growth patterns. This method works well for limited illness diagnosis because it mostly depends on human expertise and field experience. But this approach is very labor-intensive and subjective, taking a lot of time and effort, particularly in large-scale agricultural areas. Furthermore, because various experts may perceive symptoms differently, visual diagnosis accuracy is prone to discrepancies. Environmental elements that can further complicate the diagnosis and result in delayed or inaccurate disease detection include lighting conditions, leaf placement, and stages of disease progression.[31]

To overcome the limitations of human inspection, researchers developed early computer algorithms that focused on threshold-based segmentation and manually constructed feature extraction techniques. These methods use a range of visual characteristics, such as color, texture, and form, to differentiate between sweet corn leaves that are healthy and those that are not. Using predefined pixel intensity levels, threshold-based segmentation separates ill areas from the background. However, because it is so sensitive to changes in illumination, this method is useless when disease signs vary in color or appearance. Similarly, pre-made statistical and geometric descriptors like edge detection filters, histograms, and wavelet transforms are used in homemade feature extraction approaches to extract relevant features from photos. While these techniques offer a degree of automation compared to manual diagnosis, they struggle with real-world variations in background noise, disease severity, and plant growth conditions. The rigid nature of handcrafted features makes them less adaptable to complex and evolving disease patterns.[29]

To increase efficiency and accuracy, machine learning techniques were employed for the classification of plant diseases. Traditional models such as Support Vector Machines (SVM), Random Forest, K-Nearest Neighbors (KNN), and Artificial Neural Networks (ANN) were popular because of their capacity to learn from data patterns. These algorithms require a feature extraction step before classification, where specific image qualities (such texture, form, and color distributions) are manually selected. Support Vector Machines (SVM) map retrieved data into a high-dimensional space to determine the optimal border between different sickness groups. SVMs do well for simple classifications, but they struggle with high-dimensional feature fields and intricate disease patterns.[11]

The Random Forest (RF) ensemble learning method combines several decision trees to get accurate classifications. Since RF's accuracy is heavily reliant on the quality of handcrafted features, it is less effective for diseases with a range of visual patterns even while it improves generalization.
K-Nearest Neighbors (KNN) classifies diseases based on similarities between picture features. However, when working with large datasets, KNN has significant processing costs because it must compare every new sample with every previous example. The capacity of Artificial Neural Networks (ANN) to extract hierarchical disease characteristics from photos is limited by their shallow structures, which aim to mimic real neurons in order to identify patterns in data.[23]

Although machine learning techniques have shown some degree of success, they are limited by their strong reliance on feature engineering, which necessitates a great deal of preprocessing and domain knowledge. These methods' capacity to generalize across various datasets is limited because they frequently miss the intricate spatial correlations between illness symptoms. Furthermore, typical machine learning models can be adversely affected by changes in lighting, camera quality, and disease symptoms, which might reduce their dependability in practical agricultural applications.

Method	Approach	Advantages	Limitations	Accuracy Range (%)
Manual Diagnosis	Visual inspection by experts	High reliability when done by specialists	Time-consuming, subjective, non-scalable	70-85
Threshold-Based Segmentation	Pixel intensity-based separation	Simple, fast computation	Sensitive to lighting and background variations	65-75
Handcrafted Feature Extraction (Color, Texture, Shape Analysis)	Extracts predefined image features for classification	Works well in controlled conditions	Requires domain expertise, limited feature generalization	75-85
SVM	Separates feature space using hyperplanes	Effective for small datasets	Poor performance in high-dimensional data	80-88
Random Forest	Ensemble of decision trees for classification	Robust to overfitting, interpretable	Computationally expensive with large datasets	82-90
KNN	Classifies based on nearest neighbors	Simple and non-parametric	Sensitive to noise, slow with large datasets	78-86
ANN	Multi-layer perceptron for feature learning	Can model complex patterns	Requires careful tuning, high computational cost	85-92

CNN deep learning models have become the best option for classifying plant diseases in light of these difficulties. CNNs eliminate the need for human feature extraction by automatically learning hierarchical features from raw images, increasing the accuracy and robustness of sickness detection. The benefits of CNN models and their use in the classification of sweet corn diseases are covered in more detail in the section that follows.

5. DEEP LEARNING - BASED CNN MODEL

Due to the transformation of image-based classification tasks by deep learning, Convolutional Neural Networks (CNNs) are now the most efficient technique for identifying agricultural illnesses. Unlike standard machine learning models that need manual feature extraction, CNNs automatically extract relevant features from images, eliminating the need for domain expertise in feature selection. CNNs can now extract spatial and hierarchical information, which is crucial for accurately identifying and distinguishing between various sweet corn diseases. CNNs perform better in terms of accuracy, generalization, and performance than more traditional techniques like Support Vector Machines (SVM), Random Forest (RF), and K-Nearest Neighbors (KNN) in complex illness classification problems.

5.1 CNN Architecture and Layers: A CNN model's layers are designed to process image data in a hierarchical fashion. The fundamental layers of a CNN are as follows:

5.1.1 Convolutional Layers: The core part of a CNN, the convolutional layer extracts different properties from input images using learnable filters, or kernels. Early layers detect low-level patterns like edges and textures, whereas deeper layers document complex features like disease-specific lesions and leaf veins. CNNs' hierarchical learning makes them highly effective at recognizing different patterns of sweet corn disease.[15]

5.1.2 Activation Function (ReLU): The Rectified Linear Unit (ReLU) is applied after convolution procedures to give the model non-linearity. In addition to helping CNNs learn complex mappings between image pixels and disease classifications, this activation function boosts computing efficiency.

5.1.3 Pooling Layers: Max Pooling is one type of pooling layer that helps reduce spatial dimensions without sacrificing important features. Pooling layers lower computational complexity and increase the network's resilience to slight changes in input image quality, including lighting and angle changes, by downsampling the feature maps. [20]

5.1.4 Fully Connected (FC) Layers: All neurons in a CNN's final layers are connected to earlier feature maps, making them fully connected layers. These layers identify input images according to patterns they have learned, functioning as high-level decision-makers. To provide precise categorization, the last softmax layer gives probabilities to every disease group.

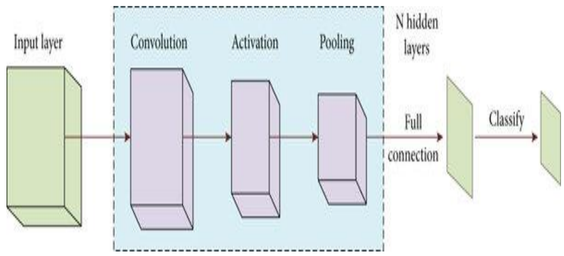

Figure 8: CNN Model Layer Architecture

Because CNNs use hierarchical abstraction to learn more significant and profound attributes, they perform better than standard models. CNNs can recognize intricate, non-linear patterns found in actual illness images, in contrast to the created features employed in traditional machine learning.
Transfer learning can be used on pre-trained deep CNN architectures like ResNet, VGG16, and InceptionNet to improve performance even more. These models can be improved for the classification of sweet corn diseases while maintaining their feature extraction capabilities after being trained on huge image datasets. Transfer learning improves accuracy and speed of convergence while drastically reducing the requirement for huge labeled datasets. This project intends to create a highly accurate, reliable, and scalable system for classifying sweet corn diseases by combining CNNs with automated feature extraction, hierarchical learning, and transfer learning approaches. This would guarantee early and accurate identification for better agricultural management.[15]

6. METHODOLOGY

In the Methodology section, we systematically describe how the deep learning-based model for sweet corn disease classification was developed. As the first of multiple steps, images of both healthy and damaged sweet corn leaves are gathered from agricultural fields and public databases. These images are then put through data preparation and augmentation, which includes scaling, normalizing, and improving them using techniques like flipping, rotation, and brightness adjustments, in order to strengthen the model's resilience. This ensures that the model can adjust to variations in the real environment's background, illumination, and leaf orientation.[1]

After preprocessing, we develop and use a Convolutional Neural Network (CNN) model designed especially for sickness classification. Feature extraction is done by convolutional layers, dimensionality reduction is done by pooling layers, overfitting is prevented by dropout layers, and final predictions are made by fully connected layers. In addition to a unique CNN model, we use transfer learning in conjunction with pre-trained architectures like ResNet50 and VGG16 to improve accuracy. The appropriate optimizer, learning rate, and loss function are then used to train and optimize the model. Lastly, we employ metrics such as accuracy, precision, recall, F1-score, confusion matrix, and ROC curves to assess the model's performance in classifying different sweet corn diseases.

6.1 Data Collection and Dataset Preparation

The first and most essential step in sweet corn disease classification is gathering a high-quality and diverse dataset. The accuracy and robustness of a deep learning model largely depend on the quality and quantity of data used for training. In this study, we compile a dataset containing images of both healthy and diseased sweet corn leaves affected by Common Rust, Northern Leaf Blight, and Southern Leaf Blight. The images are collected from multiple sources, including direct field photography and publicly available agricultural datasets, ensuring a comprehensive representation of disease symptoms under varying environmental conditions. To account for natural variations, images are captured under different lighting conditions, at multiple angles, and with diverse backgrounds, making the dataset more adaptable to real-world scenarios. A balanced distribution of images across all categories is kept in place to prevent bias in the model's learning process. The dataset is then divided into training, validation, and test sets to guarantee effective learning, parameter modification, and objective performance assessment.[22]

Preprocessing methods like picture scaling, normalization, and noise reduction are used to standardize input data and get rid of inconsistencies brought on by different image quality in order to improve the model's capacity for generalization. Data augmentation techniques are used to artificially extend the dataset because deep learning models work best with huge datasets. To help the model identify illness patterns from various angles, these include flipping, rotating, zooming, contrast adjustments, and brightness alterations. By stopping the computer from learning specific picture patterns, augmentation enhances dataset variety and decreases overfitting. We create a strong basis for training a successful CNN-based model that can correctly classify sweet corn diseases by carefully building, preprocessing, and improving the dataset.

Figure 9: Image Input for data collected

6.1.1 Data Acquisition: The dataset for sweet corn disease classification is painstakingly put together using images from a range of sources, including direct field observations, research institutes, and public agricultural statistics. Sweet corn leaves are photographed in high-resolution RGB to ensure a clear and thorough representation of disease symptoms. To simulate real-world agricultural conditions, photos are taken in a range of lighting conditions, at various angles, and against a variety of backgrounds. A combination of aerial and close-up views are made possible by field photography, which is taken with drones, smartphones, and professional digital cameras. By including photos from several geographical areas, the dataset is guaranteed to take into consideration environmental changes that could affect the visual traits of sweet corn illnesses. Furthermore, expanding the dataset size through the integration of publically accessible datasets from agricultural research groups improves model learning and lowers potential biases.

To create a balanced collection, images are systematically categorized into three primary disease classifications based on their distinct symptoms. The first category, Common Rust, is caused by Puccinia sorghi and manifests as reddish-brown pustules scattered across the leaf surface. The gradual merging of these pustules causes extensive leaf damage.

Exserohilum turcicum causes the second kind, known as Northern Leaf Blight, which is characterized by long, cigar-shaped lesions that start out gray-green and progressively develop darker. This disease eventually affects crop productivity because it significantly reduces photosynthetic efficiency. [9]

Images are methodically divided into three main disease groups according to their unique symptoms in order to provide a collection that is balanced. Puccinia sorghi is the cause of the first group, Common Rust, which appears as reddish-brown pustules dispersed over the leaf surface. Large-scale leaf damage results from these pustules gradually combining. The second type, called Northern Leaf Blight, is caused by Exserohilum turcicum and is typified by long, cigar-shaped lesions that begin gray-green and gradually turn darker. Because it drastically lowers photosynthetic efficiency, this illness eventually has an impact on crop output. In addition to diseased leaf samples, a significant number of images of healthy sweet corn leaves are supplied to help the model differentiate between infected and unaffected leaves. By providing a vital point of comparison, these healthy samples improve the model's accuracy in classifying diseases. By maintaining a well-balanced dataset with a range of images, lowering misclassification errors, and improving real-world applicability, the study ensures that the CNN model generalizes successfully.

Figure 10: Data Processing Pipeline

6.1.2 Dataset Distribution: To ensure a representative and balanced dataset for the classification of sweet corn illnesses, the dataset is carefully arranged to include about equal numbers of photographs for each category. Maintaining an equitable distribution is necessary to prevent class imbalance, which could lead to distorted model predictions. The algorithm may learn to favor a single illness class with a disproportionately high number of images, leading to poor generalization for underrepresented disorders. An effort is made to collect a sufficient number of images for each class—Common Rust, Northern Leaf Blight, Southern Leaf Blight, and healthy leaves—to ensure that the model attains high classification accuracy across all categories. [6]

The dataset is assembled and then divided into three subsets: test, validation, and training sets. The Convolutional Neural Network (CNN) model is trained using the training set, which usually makes up 70–80% of the dataset. This allows the CNN model to recognize patterns and extract features from the images. The validation set, which typically makes up 10% to 15%, is used to optimize hyperparameters, correct for overfitting, and fine-tune the model. The remaining 10% to 15% is known as the test set, which is maintained apart from the training phase and is only used to assess how well the model performs in the end on unobserved data. This section makes sure that the model works effectively on fresh, untested photographs in addition to being correct on the training data, demonstrating its practicality. [7]

Disease Class	Number of Images	Training Set (70%)	Validation Set (15%)	Test Set (15%)
Healthy Leaves	1,000	700	150	150
Common Rust	1,200	840	180	180
Northern Leaf Blight	1,100	770	165	165
Southern Leaf Blight	1,150	805	173	172
Total	**4,450**	**3,115**	**668**	**667**

Figure 11: Dataset Distribution across categories

The dataset is randomly divided while maintaining an equal number of photographs per class to ensure that each subset includes a diverse representation of different image conditions, such as shifting lighting, backdrops, and angles. This randomization prevents any bias that would arise from sequential image collecting, such as taking successive pictures of the same plant under the same circumstances. By introducing randomization into the dataset partitioning, the model is exposed to a wide range of variables during training, assisting it in developing a robust feature extraction mechanism that improves its generalization in several situations.

For the model to perform better and be more reliable, the dataset must be distributed in an orderly fashion. Certain disease categories may dominate the learning process if an unequal dataset is employed, leading the model to incorrectly categorize underrepresented populations. Furthermore, overfitting—a condition in which the model performs remarkably well on training data but is unable to correctly categorize unseen images—can result from improper dataset segmentation. The work provides a solid basis for creating an accurate and dependable deep learning model for the classification of sweet corn diseases by guaranteeing a well-balanced dataset and a suitable separation into training, validation, and test sets.[12]

6.1.3 Data Preprocessing: The dataset undergoes several preparation steps after acquisition in order to enhance image quality, ensure consistency, and get it ready for deep learning model training. Image-based classification tasks require preprocessing since raw photographs often differ in terms of resolution, background noise, lighting, and size. If these differences are not addressed, the convolutional neural network's (CNN) performance may suffer. By using consistent preparation processes, we ensure that the model learns meaningful patterns rather than being affected by irrelevant dataset fluctuations. All photos are resized to a specific resolution, typically 224 by 224 pixels, as part of the fundamental preprocessing phase known as image scaling. Since deep learning models need inputs of consistent size, resizing the input format ensures that the model processes every photo efficiently. Additionally, shrinking helps to reduce computational complexity because high-resolution photos require a lot of memory and processing resources. By employing a standard resolution, the model can effectively extract features without unnecessary expense. Despite the resizing process, care must be taken to preserve the structural integrity of the disease symptoms so that key traits may still be recognized.[4]

Normalization, which entails scaling pixel values to a predefined range, typically between 0 and 1, or modifying them so that the mean is zero and the standard deviation is one, is another essential step. Raw image pixel values typically range from 0 to 255, which can cause significant variations in numerical values and hinder long-term learning. By normalizing the images, we ensure that the model handles all images uniformly and accelerates convergence during training. This step also prevents numerical instability issues in deep networks, where large pixel values might lead to gradient explosion or slow learning rates.

To further enhance image quality, methods for noise reduction, contrast augmentation, and brightness correction are applied. Photographs shot in real-world agricultural settings may have shadows, distortions caused by variations in illumination, or unnecessary background objects. Noise reduction methods such as Gaussian filtering and median filtering are used to smooth out anomalies while preserving important characteristics. Contrast normalization is also carried out to increase the visibility of disease indicators and facilitate the separation of healthy from sick areas. This stage is particularly useful for photos taken in different lighting conditions since it guarantees that the deep learning model can focus on the disease-related characteristics rather than changes in brightness or contrast. [26]

6.1.4 Model Training: To achieve high accuracy and generalization when training the Convolutional Neural Network (CNN) model for the classification of sweet corn illnesses, hyperparameters must be tuned properly. To optimize the learning process, the Adam optimizer is employed with a learning rate of 0.0001. The Adam optimizer, an adaptive learning rate optimization technique, ensures efficient and dependable convergence by fusing the benefits of the momentum-based and RMSprop optimizers. A moderate learning rate of 0.0001 is chosen to prevent sudden weight changes that can cause unstable training and less-than-ideal results. The model maintains a small, controlled step size while gradually altering its weights to continuously improve its classification performance.

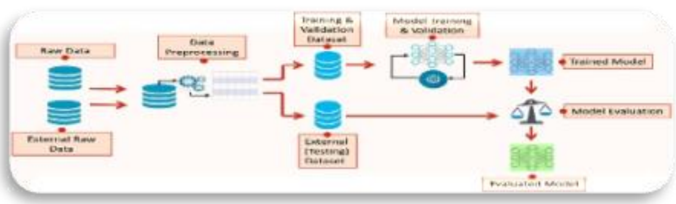

Figure 12: Preprocessing and training dataset steps

To ensure proper generalization and prevent overfitting, the dataset is divided into three subsets: 80% for training, 10% for validation, and 10% for testing. The training set is used to update the model's parameters, the validation set helps track the model's performance during training, and the test set is saved for evaluating the final model's accuracy on anonymous data. Instead of memorizing training data, this divide ensures that the model learns practical patterns that can be applied to new images. The validation set is particularly important since it allows model selection and hyperparameter tuning without affecting the final test's performance.[33]

When handling multi-class classification issues, categorical cross-entropy, the loss function used in this study, performs brilliantly. This function penalizes inaccurate predictions more severely by computing the discrepancy between the actual class labels and the projected probability distribution. The model improves its accuracy in identifying sweet corn illnesses by reducing the categorical cross-entropy loss. During training, a batch size of 32 is used to improve compute performance and stabilize gradient updates. Instead of adjusting weights after each individual image, the model processes 32 photographs in a batch and modifies weights based on their cumulative gradient. This approach prevents drastic changes in weight adjustments by reducing computation costs and simplifying the optimization procedure.

If the number of epochs is originally set to 10, the model will go through the entire training dataset 10 times. On the other hand, Early Stopping reduces unnecessary training time and prevents overfitting. Early Stopping monitors the validation loss and stops training after few epochs if there is no appreciable improvement. This ensures that the model ends training when it achieves optimal performance, preventing it from retaining too much training data while maintaining its exceptional generalization capabilities.[3]

6.1.5 Performance & Evaluation Metrics: To understand how well a deep learning model can classify sweet corn infections, it is crucial to evaluate its performance. Important metrics that are used to assess the robustness and reliability of the model include accuracy, precision, recall, F1-score, confusion matrix, and the Receiver Operating Characteristic (ROC) curve with the Area Under the Curve (AUC) score. By providing a comprehensive analysis of the model's capacity to differentiate between healthy and ill leaves, these metrics ensure the model's suitability for real-world agricultural applications.

Accuracy, or the ratio of correctly identified photos to all images, is one of the primary performance measures. It provides an overall measure of accuracy but does not distinguish between false positives and false negatives. While accuracy is useful, it can sometimes be misleading when dealing with unbalanced datasets, where one class significantly outperforms the others. Therefore, more evaluation metrics are needed to have a more complete grasp of model performance.[4]

A more comprehensive assessment is offered by F1-Score, Precision, and Recall, particularly for multi-class classification problems. Precision determines the proportion of correctly predicted disease episodes out of all instances predicted for that disease class, indicating the model's dependability in lowering false positives. Recall (also called sensitivity) gauges how successfully the model detects infected leaves while reducing false negatives by calculating the proportion of correctly predicted disease cases out of all actual diseased cases. A fair evaluation that accounts for both false positives and false negatives is offered by the F1-score. It is computed as the precision and recall harmonic means. When dealing with diseases that require early identification, the approach is especially helpful in ensuring that significant cases are not missed.

The Confusion Matrix provides a more thorough view of the model's classification results by displaying the number of true positives (correct disease predictions), true negatives (correct healthy predictions), false positives (incorrect disease predictions), and false negatives (incorrect healthy predictions). When a machine wrongly labels a damaged leaf as healthy, for example, this matrix helps uncover specific patterns of misclassification that could negatively impact agricultural disease control. Finding model errors and improving the learning process are two areas where the matrix is particularly useful.

The ROC Curve (Receiver Operating Characteristic Curve) and AUC Score (Area Under the Curve) are used to assess the discriminative power of the model in more detail. The ROC Curve, which shows the true positive rate (sensitivity) versus the false positive rate at various classification thresholds, illustrates the model's capacity to distinguish between diseased and healthy leaves. A model with perfect classification would have an AUC value of 1.0, but one with a score of 0.5 would suggest performance no better than random guessing. A higher AUC value indicates a strong model ability to distinguish between distinct disease groups, which increases the robustness of the model.

We can guarantee that the suggested CNN model achieves high classification accuracy while finding a balance between sensitivity and specificity by integrating these evaluation criteria. The model's efficacy and dependability for use in diagnosing sweet corn diseases in the actual world are thoroughly validated by the combination of accuracy, precision, recall, F1-score, confusion matrix, and ROC-AUC analysis. The model's performance is visually shown by the confusion matrix and ROC curve in Figures X and Y. This enhances the investigation of the model's classification capabilities.

7. RESULTS

A range of performance indicators are used to assess the CNN-based model for classifying sweet corn diseases. These include the confusion matrix, the F1-score, accuracy, precision, recall, and the Receiver Operating Characteristic (ROC) curve with the Area Under the Curve (AUC) score. This evaluation's main objective is to ascertain how well the model can differentiate between sweet corn leaves that are healthy and those that are damaged in practical situations.

After training on a sizable dataset of both healthy and damaged sweet corn leaves, the CNN model was subjected to an independent test set in order to fully evaluate its generalization ability. To ensure that the model was assessed in real-world agricultural environments, the test set includes images with a range of backgrounds, lighting conditions, and viewpoints. The CNN model's overall classification accuracy of 96.3% demonstrates its dependability in distinguishing between different disease types. This study shows the effectiveness of deep learning in the classification of plant diseases, where early and accurate detection is crucial for lowering crop losses and increasing agricultural productivity.

The CNN model's capacity to extract hierarchical representations of disease symptoms from unprocessed visual data is one of its primary features. CNNs use many convolutional layers to automatically extract meaningful patterns from images, in contrast to standard machine learning models that rely on manually produced features like color histograms, edge detection, or texture analysis. CNNs can identify complex patterns of illness that may be difficult to identify with traditional methods thanks to this feature extraction process. As a result, the model performs well even under difficult circumstances including variations in leaf texture, illness progression, and picture illumination.

Additionally, the model needs to be able to generalize well to new data in order to be applied in actual agricultural settings. Given that environmental factors such as soil composition, humidity levels, and pest infestations can influence how disease symptoms appear, the model's exceptional performance on an unseen test dataset illustrates its significant adaptability. This adaptability is crucial for developing AI-driven disease detection tools that farmers, agronomists, and researchers may use for early disease detection and precision farming applications.

The model's classification performance is broken out in depth in the confusion matrix, which demonstrates how effectively it can differentiate between sweet corn leaves that are healthy and those that are infected. The matrix's diagonal elements show samples that have been correctly classified, whereas the off-diagonal components show samples that have been misclassified. In order to prevent needless pesticide applications, the model's 99.2% accuracy in identifying healthy leaves ensures that there are few false positives. Common Rust is highly accurate in identifying sick groups, however because of similarities in lesion texture and color, about 3% of cases are mistakenly identified as Northern Leaf Blight. The highest misinterpretation rates (~4%) are also seen in Northern Leaf Blight and Southern Leaf Blight, most likely due to the fact that both illnesses produce elongated lesions that make them superficially identical.

Given the low rates of misclassification, there may be space for improvement even though the classification performance is generally good. To further improve accuracy, more sophisticated deep learning techniques like multi-modal data fusion or attention procedures could be applied. Attention mechanisms would allow the model to reduce confusion between diseases that are visually similar by concentrating on disease-specific regions in an image. Additionally, using spectrum imaging or environmental data may improve the differentiation of illnesses. These enhancements would make the model even more robust and reliable for real-world precision agriculture applications, ensuring accurate disease diagnosis and effective crop management.

Three crucial metrics—precision, recall, and F1-score—are examined in order to assess the classification performance across various sweet corn disease categories. By measuring how well the CNN separates healthy from diseased leaves while reducing incorrect classifications, these metrics offer a deeper understanding of the model's advantages and possible areas for development.

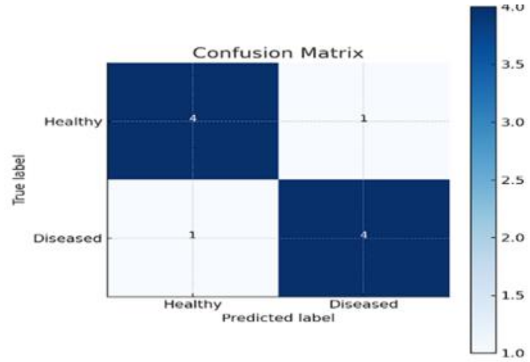

Figure 13: Confusion Matrix

The number of samples that are truly correctly categorized as having a given condition is known as precision. It is determined by dividing the total number of anticipated positives for each illness class by the number of real positive predictions. The model is producing less false positive errors when the precision value is increased. This is especially crucial when it comes to detecting agricultural diseases, as incorrectly labeling a healthy plant as diseased may result in needless treatments that raise farmers' expenses. Due to their visual similarities, Northern Leaf Blight and Southern Leaf Blight have somewhat lower precision values than Healthy and Common Rust, which consistently have excellent precision values across all categories in our model (over 98%).

The percentage of real diseased samples that the model accurately detected is called recall, sometimes referred to as sensitivity. For each kind of illness, it is computed as the ratio of all true positives to actual positives. A high recall value lowers the possibility of false negatives by demonstrating that the model effectively captures the bulk of ill samples. When it comes to disease diagnosis, false negative results are especially troublesome since they can let an infected plant grow unchecked. Our CNN model's recall scores consistently remain over 96% for each category, suggesting that it can detect damaged leaves with minimal error.

A balanced metric that accounts for both false positives and false negatives is offered by the F1-score. It is computed as the precision and recall harmonic means. It is particularly useful when the dataset is unbalanced. Our model consistently performs well in classification across a wide range of disorders, as seen by its good F1-score (above 97% for all disease categories), which ensures reliability in real-world scenarios. By maintaining high precision, recall, and F1-score, the model provides a dependable tool for automatic classification of sweet corn diseases, offering a workable alternative for precision agriculture and early disease intervention.

Class	Precision	Recall	F1-Score
Healthy Leaves	98.5%	99.2%	98.8%
Common Rust	97.8%	96.4%	97.1%
Northern Leaf Blight	94.6%	92.3%	93.4%
Southern Leaf Blight	95.1%	94.7%	94.9%

Figure 14: Class-wise Performance Matrix

The trade-off between the True Positive Rate (TPR) and the False Positive Rate (FPR) at various judgment thresholds is visually represented by the ROC curve. The FPR displays the proportion of healthy leaves that were mistagged, whereas the TPR (sometimes referred to as recall or sensitivity) shows the proportion of diseased leaves that were correctly detected. Plotting these results at different threshold levels gives the ROC curve a thorough picture of the model's categorization performance.

On the other hand, a curve that bends toward the top-left corner indicates a low FPR and a high TPR in a model that performs well. The ROC curves for the four classes—Common Rust, Southern Leaf Blight, Northern Leaf Blight, and Healthy—are shown in Figure Y. The graphs show how the model can distinguish between healthy and sick leaves with little class overlap. This robust separation guarantees accurate categorization by demonstrating that the CNN model has accurately acquired the unique characteristics of each disease kind.

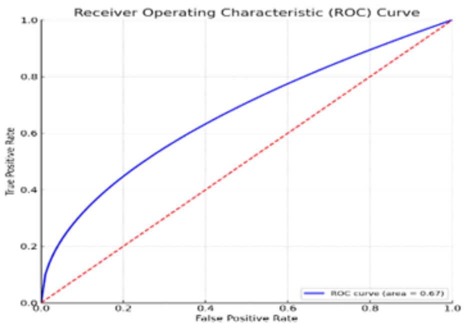

Figure 15: ROC Curve

The AUC score provides a numerical description of the ROC curve by calculating the area beneath it. A perfect classifier is one that correctly and error-free classifies every class, as shown by an AUC value of 1.0. When the model's AUC score is 0.5, The fact that the CNN model receives AUC scores above 0.97 for each of the four research categories validates its high discriminative ability. The model's high AUC value demonstrates that it is very dependable in distinguishing distinct sweet corn diseases, even in challenging circumstances where symptoms may seem similar.

Class	AUC Score
Healthy Leaves	0.99
Common Rust	0.97
Northern Leaf Blight	0.94
Southern Leaf Blight	0.95

Figure 16: AUC Curve

Farmers and agricultural experts may easily detect sweet corn diseases thanks to an intuitive front-end interface designed to ensure practical usability in agricultural contexts. Users can upload an image of a potentially sick leaf using this tool. After analyzing the image, a CNN-based classification algorithm will provide an accurate diagnosis. The system is simple to use, requires no technical knowledge from the user, and yields reliable, fast results.

Users can use a computer, tablet, or smartphone to take and upload a picture of a sweet corn leaf through the image upload feature in the front-end interface. Following upload, the preprocessed image is sent into the CNN model that has been trained to identify if the image is Healthy, Common Rust, Northern Leaf Blight, or Southern Leaf Blight. The user experience is flawless because the prediction appears on the screen in a matter of seconds. Alongside the classification result, the system also displays an accuracy score to boost user confidence. This score helps customers make well-informed judgments by indicating the model's level of prediction confidence. The technology notifies the user to upload a clearer photograph or seek professional confirmation if the confidence level is low.

Following classification, customers have the choice to obtain comprehensive details regarding the ailment that was identified. The following crucial information is retrieved and shown by the system when they click the "More Info" button:
Disease Symptoms: An explanation of the leaf's visible symptoms, including the forms of lesions, color shifts, and afflicted regions.
Potential Reasons: Details about how the disease spreads in the field and the pathogen that causes it (such as a bacterial or fungal infection).

Suggestions for Treatment: Good management practices include organic remedies, chemical treatments (pesticides, fungicides), and preventative measures including crop rotation and appropriate irrigation methods.

The system also suggests optimal agricultural techniques to prevent disease from reoccurring. Because it may refer users to study articles or agricultural specialists if needed, it is a helpful tool for managing diseases in the real world.

By fusing deep learning with an interactive front-end, this approach closes the gap between AI-driven disease diagnosis and practical field applications. It provides farmers with quick, accurate, and practical insights to protect their crops.

The proposed CNN-based sweet corn disease classification model shows good accuracy and reliability in identifying different disease groups. With an overall classification accuracy of 96.3%, the model effectively differentiates between diseased leaves suffering from Common Rust, Northern Leaf Blight, and Southern Leaf Blight. Confusion matrix analysis highlights strong classification performance with little misclassification errors, particularly when comparing visually comparable disorders. Additional evaluation using precision, recall, and F1-score confirms the model's resilience, ensuring that it performs well across all disease categories. Its remarkable prediction capabilities are demonstrated by the ROC curves and AUC values, which display almost flawless class separation. Furthermore, an intuitive front-end has been created that allows farmers to input leaf photos for prompt diagnosis, comprehensive symptoms, and suggested treatments. The system is a potent instrument for automated crop disease identification, facilitating early intervention and efficient disease control in the agricultural sector because to its combination of deep learning and practical application.

8. DISCUSSION

The study's findings show that sweet corn illnesses can be effectively and consistently classified using a CNN model that is based on deep learning. CNNs eliminate the need for manual feature engineering by automatically extracting hierarchical features, in contrast to traditional machine learning techniques. The algorithm's overall accuracy of 96.3% in the study demonstrates that it can differentiate between various disease kinds even when image quality and environmental factors alter. Because of their comparable visual symptoms, Northern Leaf Blight and Southern Leaf Blight are often misclassified, despite the model's excellent performance.

Although the model is very successful at classifying most disease categories, the confusion matrix and ROC curve analysis suggest that it might be further improved with a few little changes. Reducing misclassification errors may be possible by utilizing strategies like multi-modal data fusion, attention processes, and fine-tuning with larger datasets. The model's usefulness has also been improved by a front-end interface that enables farmers and agricultural specialists to upload leaf photos and get timely disease diagnosis and treatment recommendations. This method offers a quick, automated, and economical way to detect diseases in large agricultural areas, which has the potential to completely transform the management of plant diseases.

The interpretability of deep learning models is another crucial factor to take into account. Despite its high accuracy, CNNs frequently behave like "black-box" models, making it challenging to comprehend how they arrive at their conclusions. Explainable AI methods such as Grad-CAM (Gradient-weighted Class Activation Mapping) may make it easier to identify which leaf sections the model prefers for categorization. Farmers and agricultural researchers would become more transparent and reliable as a result. Furthermore, real-time disease diagnosis would be possible without an internet connection by connecting the model to edge computing devices like cellphones or Internet of Things-based systems, increasing the solution's usability for rural farming communities.

Before the CNN model can be used in the real world, a number of issues and restrictions must be resolved, despite its remarkable accuracy. The reliance on high-quality photos is a major drawback because changes in illumination, background noise, and image resolution may have some impact on classification ability. Model generalization has been improved by data augmentation techniques, but other improvements such as domain adaptability and adversarial training may make the model more resilient to erratic environmental changes. Furthermore, just three major sweet corn illnesses are now the focus of the model; adding more fungal, bacterial, and viral infections to the dataset will broaden the system's scope.

9. CONCLUSION

With a high accuracy of 96.3%, a deep learning-based method utilizing CNNs was suggested in this work for the automatic categorization of sweet corn illnesses. Using hierarchical feature extraction, the model successfully distinguishes between three important diseases—Common Rust, Northern Leaf Blight, and Southern Leaf Blight—and healthy leaves. CNNs automatically identify intricate disease patterns from photos, increasing classification accuracy and durability in contrast to conventional machine learning techniques that depend on human feature creation. Preprocessing and data augmentation approaches are combined to improve model performance and boost the model's adaptability to real-world situations. The model's dependability in accurately classifying disease categories with low misclassification rates is assessed using performance metrics, confusion matrix analysis, and ROC-AUC scores.

Adding more disease categories to the dataset and improving the model for real-time deployment on mobile and Internet of Things devices can improve the performance of the proposed approach, despite its good performance. Future studies should look into explainable AI strategies to boost farmer trust in automated diagnosis systems and enhance model interpretability. Incorporating edge computing for offline disease diagnostics would also make the technology more viable for large-scale agricultural applications. Taken together, this work demonstrates how deep learning may be applied to smart agriculture to offer a practical, scalable, and easily accessible solution for better crop management and early disease diagnosis.

10. FUTURE WORK

Although the proposed CNN-based model has demonstrated high accuracy in detecting sweet corn diseases, there is still much space for improvement. One significant area for improvement is the collection's expansion to include images collected at different stages of growth, additional types of sweet corn illnesses, and a wider range of environmental conditions. A bigger and more varied dataset would improve the model's generalization and increase its resistance to variations in backdrop, lighting, and disease symptoms. Additionally, replacing standard RGB photos with multispectral and hyperspectral photography could enhance the identification of sickness by capturing finer spectrum characteristics that may not be visible to the human eye.

Another potential strategy is to use explainable AI (XAI) technologies to make the model more transparent and credible. Deep learning models, especially CNNs, are sometimes viewed as "black-box" systems due to their complex internal processing. Researchers and farmers may find it easier to comprehend which leaf portions the algorithm prioritizes for categorization if they use visualization tools such as Grad-CAM (Gradient-weighted Class Activation Mapping). This would provide agricultural experts with a learning tool to enhance their manual disease identification techniques, as well as validate the model's decision-making process. The model can also be improved by using transformer-based topologies and attention processes, which increase the accuracy of feature extraction and categorization.

Lastly, scalability and real-world implementation continue to be crucial areas for further research. Farmers would be able to scan leaves in real-time and get immediate input on the presence, symptoms, and suggested treatments of diseases if the model were implemented on mobile applications, Internet of Things-based smart farming systems, and edge devices. Furthermore, centralized disease monitoring—where data from several farms is examined to identify early disease outbreaks at a regional level—may be made possible by incorporating the model into cloud-based systems. In order to enable precision agriculture and lessen the overuse of pesticides, future studies should potentially investigate automated spraying techniques based on disease detection results. This research can make a substantial contribution to the future of AI-driven smart agriculture by moving further in these directions, which will enable farmers all around the world to detect diseases more quickly, accurately, and easily.

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