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Disease Detection in Corn or Maize Plant Leaves Using Specim Iq Hyperspectral Imaging and Proposed Dnn Classifiers with Alexnet

Praba V[1], Dr. Krishnaveni K[2]

[1]Research Scholar, Department of Computer Science, Sri S.Ramasamy Naidu Memorial College, (Affiliated to Madurai Kamaraj University, Madurai), Sattur,Tamilnadu, India, praba@srnmcollege.ac.in
[2]Associate Professor & Head, Department of Computer Science, Sri S. Ramasamy Naidu Memorial College, (Affiliated to Madurai Kamaraj University, Madurai), Sattur, Tamilnadu, India, kkrishnaveni@srnmcollege.ac.in

It is essential to identify illnesses in corn and maize plants early on in order to preserve crop health and guarantee agricultural output. This work investigates the detection of plant diseases in leaves using advanced deep learning techniques in conjunction with Specim IQ hyperspectral imaging. We compare the performance of a newly constructed classifier, DeepIncepNet, with other state-of-the-art models, such as InceptionV3, ResNet-50, and ResNet-101. We also present a novel Deep Neural Network (DNN) classifier based on the AlexNet architecture. Preprocessing was done on hyperspectral imaging data to improve image quality and retrieve pertinent characteristics. A large dataset was used to train and verify the classifiers, and the results showed excellent disease detection accuracy. The comparative analysis illustrates the benefits and drawbacks of each model, highlighting the possibility for accurate and effective plant disease diagnosis through the combination of deep learning and hyperspectral imaging—a major improvement over conventional techniques.

Keywords: Corn Disease Detection, Maize Plant Leaves, Specim IQ Hyperspectral Imaging, Deep Neural Networks (DNN), AlexNet, InceptionV3, ResNet-50, ResNet-101, Image Classification, Precision Agriculture.

1. Introduction

In order to maintain food security and the global economy, agriculture is essential. Among the most extensively grown crops are corn and maize, which are used as essential ingredients in many industrial goods and as staple foods. Nevertheless, a number of illnesses can seriously affect the quality and output of these crops. For plant diseases to be effectively managed and controlled, to minimize financial losses, and to ensure sustainable agricultural practices, early detection and diagnosis are crucial. Conventional illness detection techniques, which mostly

rely on visual inspection and laboratory testing, are frequently labor-intensive, time-consuming, and prone to human error. New paths for the development of automated, effective, and precise plant disease detection systems have been made possible by recent developments in machine learning and image technology [1] [2]. Particularly, hyperspectral imaging has shown to be an effective method for gathering comprehensive spectral data over a broad range of wavelengths, allowing for the detection of minute alterations in plant physiology that may be signs of illness.

Cutting-edge technology is included in the Specim IQ hyperspectral imaging device, which can produce high-resolution images with rich spectral data. In order to identify diseases in the leaves of corn and maize plants, this study makes use of the capabilities of Specim IQ hyperspectral imaging in conjunction with cutting edge deep learning techniques [3]. Deep Neural Networks (DNNs) have shown impressive results in picture classification tasks, and there is a lot of potential for using DNNs to identify plant diseases [4]. We present a new deep neural network (DNN) classifier built on the AlexNet architecture and compare it to several well-known models such as InceptionV3, ResNet-50, ResNet-101, and a recently created classifier called DeepIncepNet. Our goal is to determine the best method for precise and effective disease diagnosis in corn and maize plants by assessing how well these models perform on hyperspectral imaging data.

We present a new deep neural network (DNN) classifier built on top of the DeepAlexNet architecture and compare it to several well-known models such as InceptionV3, ResNet-50, ResNet-101, and a recently created classifier called DeepIncepNet. Our goal is to determine the best method for precise and effective disease diagnosis in corn and maize plants by assessing how well these models perform on hyperspectral imaging data. By creating and assessing a unique DNN classifier for disease identification in corn and maize plants, this research uses the potential of hyperspectral imaging to advance the field of agricultural technology. The study enhances early disease detection, precision agriculture methods, and sustainable farming through thorough comparative analysis and empirical confirmation. We detail the materials and procedures utilized in this investigation, review relevant literature, present and analyze the experimental data, and end with important conclusions and directions for future research in the sections that follow.

2. Related Works

Because hyperspectral imaging (HSI) can collect fine-grained spectral information from plants, it has been extensively explored and used in agricultural sciences. With the aid of this technology, minute physiological alterations that are frequently undetectable to the unaided eye can be detected. Its efficacy in detecting plant diseases, evaluating crop health, and tracking environmental conditions has been demonstrated in a number of studies.Mahlein et al. (2012) [5], for example, showed how hyperspectral imaging may be used to identify and distinguish between a range of plant illnesses, including fungal infections in the leaves of sugar beet plants. The study highlighted how spectral signals unique to a given disease can be captured by HSI and utilized for monitoring and early identification. Analogously, Sankaran et al. (2010) [6] examined several optical sensing technologies, highlighting hyperspectral imaging's benefits over conventional techniques for plant disease diagnosis.

Convolutional Neural Networks (CNNs), a type of deep learning, have completely changed agricultural picture analysis. CNNs have shown useful in the identification, categorization, and phenotyping of plant diseases. Complex agricultural photos can be processed by CNNs due to their capacity to extract features hierarchically. Using a dataset of 54,306 photos, one of the groundbreaking research by Mohanty et al. (2016) [7] used deep learning techniques to identify 26 distinct illnesses in 14 crop species. The study's excellent accuracy rates show how reliable CNNs are for use in agricultural settings. Furthermore, Kamilaris and Prenafeta-Boldú (2018) [8] offered an extensive examination of deep learning applications in agriculture, emphasizing the technology's promise in a number of areas, such as soil analysis, yield prediction, and disease detection.

The combination of deep learning algorithms with hyperspectral imaging has demonstrated considerable potential in improving illness detection. This combination makes use of deep learning algorithms' potent feature extraction capabilities as well as the rich spectrum data that HSI provides. The application of a CNN model for hyperspectral image classification of healthy and diseased tomato leaves was investigated by Zhang et al. (2019) [9]. Compared to typical RGB photos, the study found that using hyperspectral data in conjunction with CNNs enhanced the accuracy of disease identification. Additionally, Rumpf et al. (2010) [10] emphasized the benefits of this integrated approach by demonstrating the possibility of HSI in conjunction with machine learning approaches for the early diagnosis of fungal infections in wheat.

To ascertain which deep learning architectures are best suited for agricultural applications, numerous studies have examined various models. Among the architectures that are frequently compared are ResNet-101, InceptionV3, AlexNet, and ResNet-50. AlexNet was first presented by Krizhevsky et al. (2012) [11], greatly enhancing picture classification benchmarks and opening the door to more intricate structures. Szegedy et al. (2016) [12] introduced InceptionV3, which used aggressive regularization approaches and factorized convolutions to obtain greater accuracy with fewer parameters. In order to address the vanishing gradient issue, He et al. (2016) [13] created ResNet, which added residual learning and made it possible to train extremely deep networks. The efficacy of ResNet-50 and ResNet-101 in a range of image classification tasks, including those related to agriculture, was proved by their advancements.

Even with these developments, there are still a number of obstacles to overcome in the agricultural use of deep learning and hyperspectral imaging. These include the high expense of hyperspectral equipment, the complexity of data processing and analysis, and the requirement for huge labeled datasets for deep learning model training. Subsequent investigations ought to concentrate on constructing extensive datasets, lowering the cost of hyperspectral imaging devices, and improving the interpretability of deep learning models. These technologies' usability and influence on sustainable farming will be further enhanced by their integration with precision agriculture approaches.

3. Materials and Methods

3.1. Specim IQ Hyperspectral Imaging Device

The cutting-edge, portable Specim IQ hyperspectral imaging gadget is made for collecting and

evaluating hyperspectral data for a variety of uses, such as industrial quality control, forensics, agricultural, and environmental monitoring. To make on-site data gathering and analysis easier, this gadget combines user-friendly features with hyperspectral imaging technology [14].

The 400 nm to 1000 nm spectral range is covered by the Specim IQ. A vast range of materials and circumstances can be detected within this range, which spans the visible spectrum and the near-infrared area. With the capacity to record precise spectral data throughout 204 bands, the gadget provides great spectral resolution. For applications like the detection of plant diseases, this fine resolution makes it possible to identify minute variations in spectral fingerprints. Specim IQ boasts a sensor that can capture images at 512 x 512 pixels, meaning it offers great spatial resolution. The complete spectrum is present in every pixel, enabling a thorough spatial study of the target region. With its quick data gathering design, the gadget can quickly capture hyperspectral images. When gathering data quickly is required in the field, this high-speed imaging capability is crucial. With a tiny form factor and a weight of about 1.3 kg, the Specim IQ is very portable and can be used in a variety of field settings. Its ergonomic design makes handling and using it simple. With the Specim IQ's touchscreen display and built-in computer, users can examine and analyze hyperspectral data right on the device. This feature streamlines the workflow by doing away with the requirement for external computers or intricate data transmission procedures. The gadget has an easy-to-use user interface with menus and settings that are intuitive to explore. Quick setup and execution of measurements, real-time data review, and parameter adjustment for imaging are all possible. Specim IQ has a rechargeable battery that lasts for several hours before needing to be charged again. This guarantees continuous use throughout extended periods of data collecting and field surveys. The gadget supports multiple data transfer mechanisms, including USB and Wi-Fi, and has plenty of onboard storage for hyperspectral data. This makes sharing and backing up gathered data simple [15].

Specim IQ uses the spectral signatures of several pathogens to detect and categorize plant illnesses. This feature makes it possible to monitor and detect illnesses in crops like corn and maize early on. By identifying stressors including nutrient shortages, water stress, and pest infestations, the device can evaluate the general health of crops.

3.2. Data Collection Process

Data collection was conducted under a variety of conditions to ensure the robustness and generalizability of the hyperspectral imaging and deep learning models:

• Weather: High levels of sunlight and clear skies are perfect for taking sharp hyperspectral photos.

• Crop Health Status: Data from healthy, well-maintained plants with ideal growing circumstances serve as baseline comparisons for Healthy Plants. Plants that display indications of diverse diseases (such as bacterial, viral, or fungal infections) at varying degrees of severity are referred to as diseased plants.

• Soil and Irrigation Conditions: Information gathered from fields with different types of soil (clayey, sandy, and loamy) in order to determine how soil characteristics affect hyperspectral signals. Information from fields using drip, sprinkler, and rain-fed irrigation techniques to

evaluate how water availability affects plant health and disease detection.

Data Collection Procedure

• Initial Calibration: To guarantee correct spectrum data gathering, calibration panels were used at the agricultural research site to calibrate the Specim IQ hyperspectral imaging device.

• Field Data Collection: In situ hyperspectral photos of corn and maize leaves were taken using the instrument. To standardize data collecting, images were captured at regular intervals and angles. Using portable sensors, environmental metadata (temperature, humidity, and soil moisture) was captured for correlation with hyperspectral data.

• Data Labeling: Visual inspection and professional diagnosis were used to label the hyperspectral pictures that were collected. The kind, severity, and plant growth stage of any disease were noted next to each image. To produce an extensive dataset, labels for stressed and healthy plants were also added.

• Data Management and Storage: Safe, large-capacity storage systems were used to store hyperspectral data. Data loss was avoided by performing regular backups. To enable effective data retrieval and analysis, the information, annotations, and hyperspectral pictures were managed and organized in a centralized database.

The technique of gathering data was carefully designed and carried out to guarantee the acquisition of superior hyperspectral photographs in a variety of settings. The gathered information serves as the basis for the suggested deep neural network classifiers' training and validation, which will ultimately improve the precision and dependability of disease detection in corn and maize plants[16].

3.3. Preprocessing of Hyperspectral Images

Before feeding hyperspectral pictures into deep neural network (DNN) classifiers, preprocessing is an essential step to guarantee data quality and consistency. Calibration, noise reduction, normalization, and feature extraction are common preprocessing procedures for hyperspectral pictures [17] [18]. The preparation workflow is described in full below:

1. Radiometric Calibration

Radiometric calibration is performed to convert raw digital numbers (DN) captured by the hyperspectral camera into reflectance values (R), which are independent of the sensor and environmental conditions.

- Dark Current Correction: Subtract the dark current image (captured with the lens cap on) from the raw hyperspectral image to remove sensor noise.

$$I_{corrected} = I_{raw} - I_{dark}$$

WhereI_{raw} is the raw hyperspectral image, and I_{dark} is the dark current image (captured with the lens cap on).

- Flat Field Correction: Use a white reference panel with known reflectance properties to correct for variations in illumination and sensor sensitivity across the spectral range.

$$R = \frac{I_{corrected}}{I_{white}}$$

Where, $I_{white}$is the image of a white reference panel with known reflectance properties.

2. Noise Reduction

Environmental elements and electrical sensor noise are two common causes of noise in hyperspectral photographs. Techniques for reducing noise contribute to improving the signal-to-noise ratio (SNR).

- Spectral Smoothing:Utilize spectrum smoothing methods to minimize high-frequency noise in the spectral data, such as Savitzky-Golay filtering. Employing the Savitzky-Golay filter:

$$\hat{y}_i = \sum_{j=-m}^{m} c_j \, y_{i+j}$$

- Spatial Filtering: Use spatial filters like median or Gaussian filters to smooth the image while preserving edges and important features. Applying a Gaussian filter,

$$G(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

Where,σ is the standard deviation of the Gaussian distribution.

3. Normalization

Normalization ensures that the data from different images and sessions are comparable by scaling the spectral values to a consistent range.

- Min-Max Normalization: Scale the reflectance values of each spectral band to a range of [0, 1] using min-max normalization.

$$R' = \frac{R - R_{min}}{R_{max} - R_{min}}$$

Where R is the reflectance value, R_{min} and$R_{max}$are the minimum and maximum reflectance values in the dataset.

- Standardization: Standardize the spectral data by subtracting the mean and dividing by the standard deviation for each spectral band.

$$R'' = \frac{R - \mu}{\sigma}$$

Where,μ is the mean reflectance and σ is the standard deviation.

4. Spectral and Spatial Feature Extraction

Feature extraction reduces the dimensionality of hyperspectral data while retaining essential information for classification.

- Principal Component Analysis (PCA): Apply PCA to reduce the number of spectral bands by transforming the original data into a set of orthogonal principal components that capture the most variance in the data.

Z=X | W

Where,X is the centered data matrix, W is the matrix of eigenvectors, and Z is the matrix of principal components.

- Band Selection: Select specific spectral bands that are most informative for disease detection based on prior knowledge or feature selection algorithms.

MI(X; Y) =H(X) −H (X|Y)

Where, MI is the mutual information, H(X) is the entropy of the spectral band X, and H(X|Y) is the conditional entropy given the label Y.

5. Image Segmentation

Image segmentation isolates the regions of interest (e.g., plant leaves) from the background, facilitating focused analysis.

- Thresholding: Use thresholding techniques to segment the plant leaves from the background based on reflectance values.Using Otsu's method,

$$\sigma_B^2(t) = w_1(t)w_2(t)[\mu_1(t) - \mu_2(t)]^2$$

Where, σ_B^2 is the between-class variance, w_i are the class probabilities, and μ_i are the class means.

- Morphological Operations: Apply morphological operations (e.g., erosion, dilation) to refine the segmented regions and remove small artifacts.Applying erosion and dilation:

E(A)=A⊖ B

D(A)=A⊕B

Where, A is the segmented image and B is the structuring element

6. Data Augmentation

Data augmentation increases the diversity of the training dataset by applying transformations to the hyperspectral images.

- Geometric Transformations: Apply geometric transformations such as rotations, translations, and scaling to create variations of the original images.

$$T_\theta = \begin{bmatrix} \cos\theta & -\sin\theta & 0 \\ \sin\theta & \cos\theta & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Where, θ is the rotation angle.

- Spectral Augmentation: Introduce variations in spectral data by adding synthetic noise or slightly shifting the spectral bands.

$R_{aug}=R+\epsilon$

Where, ϵ is Gaussian noise with mean μ and standard deviation σ.

7. Patch Extraction

For efficient training of DNN classifiers, hyperspectral images are often divided into smaller patches.

- Patch Size: Define an appropriate patch size (e.g., 32x32 or 64x64 pixels) that captures sufficient spatial and spectral information for disease detection.

- Patch Extraction: Extract overlapping or non-overlapping patches from the hyperspectral images, ensuring that each patch contains meaningful data.Define patch size p×p, and extract patches with stride s:

$$\text{Patches} = \{I(i{:}\, i + p - 1, j{:}\, j + p - 1) | i, j = 1, s, 2s, \dots\}$$

8. Data Annotation

Accurate labeling of the preprocessed data is essential for supervised learning.

- Expert Annotations: Collaborate with agricultural experts to annotate the preprocessed hyperspectral images with disease labels, severity levels, and other relevant information.

- Automated Labeling: Use automated techniques (e.g., clustering, unsupervised learning) to assist in labeling large datasets, followed by expert validation.

9. Data Storage and Management

Organize and store the preprocessed data in a structured format for efficient retrieval and analysis.

- Database Management: Use a database management system to store the preprocessed images, metadata, and annotations.

- Data Backup: Implement regular backup procedures to prevent data loss and ensure data integrity.

Hyperspectral picture preprocessing entails a number of procedures to guarantee data quality, minimize noise, and extract pertinent features. In order to improve the effectiveness of DNN classifiers in identifying illnesses in the leaves of corn and maize plants, this procedure is essential [19]. Effective disease control in agriculture can be aided by meticulously calibrating, normalizing, and enhancing the hyperspectral data. This will produce more accurate and dependable results in the analysis that follows.

3.4.DNN Classifiers

Because Deep Neural Networks (DNNs) can learn hierarchical features from raw data, they are effective tools for picture classification tasks. In this study, we evaluate multiple deep neural network designs (DNN) for the job of disease identification in corn and maize plant leaves using hyperspectral images: InceptionV3, ResNet-50, ResNet-101, and a custom-designed network called DeepIncepNet.

- InceptionV3 [20] [21]is a more developed variant of the Inception network that is intended to effectively expand the network's breadth and depth. Its architecture makes use of inception modules, which execute numerous convolutions in parallel with varying kernel sizes before concatenating the output. In order to speed up training and increase accuracy, it also incorporates batch normalization and adds additional classifiers to enhance convergence during training. The main characteristics of InceptionV3 are its memory and computational efficiency, as well as its parallel convolutional routes, which enable it to capture multi-scale information. Because it can capture a variety of spectral-spatial information, InceptionV3 is ideally suited for hyperspectral picture analysis.

- ResNet-50[22] [23]is a well-known 50-layer deep residual network that can train extremely deep networks. Each residual block in the architecture consists of two or three convolutional layers, and each block has shortcut connections that bypass one or more layers. The vanishing gradient issue is addressed by ResNet-50's key characteristics, which enable the training of deeper networks. Gradient flow is enhanced by identity mappings made possible by the shortcut connections. This is why ResNet-50's depth and capacity to learn intricate characteristics make it useful for hyperspectral picture categorization.

- ResNet-101 [24] [25]is a 101-layer, expanded version of ResNet-50 that offers more depth for intricate feature learning. The architecture retains batch normalization and shortcut connections, although it has more residual blocks than ResNet-50. Greater depth, which enables more thorough feature extraction, and a larger model capacity, which enables the model to capture more complex patterns in hyperspectral data, are two of ResNet-101's primary characteristics. ResNet-101 is therefore perfect for hyperspectral pictures, where precise illness diagnosis depends on fine-grained features.

- DeepIncepNetis a specially created deep learning model that blends deeper architectures with features from Inception networks. Its architecture combines deeper layers akin to ResNet for collecting complex patterns and inception modules for multi-scale feature extraction. To improve training performance and stability, it also has auxiliary branches. Combining the advantages of residual connections and inception modules, as well as balancing computational efficiency and feature learning power, are some of DeepIncepNet's key features. Because of this, DeepIncepNet is especially designed for hyperspectral image analysis, offering reliable results for the identification of diseases in maize and corn leaves.

For hyperspectral image classification, the DNN classifiers—InceptionV3, ResNet-50, ResNet-101, and DeepIncepNet—offer a variety of topologies and functionalities. This study compares different models in an effort to determine which method best utilizes deep learning and hyperspectral imaging technologies to detect diseases in corn and maize plants early on.

4. Proposed Methodology

4.1. DeepAlexNet: Proposed DNN Classifiers with AlexNet

Using hyperspectral imaging data, the suggested deep neural network (DNN) classifiers, called DeepAlexNet, offer a novel method for disease identification in the leaves of maize or corn plants. By improving AlexNet's basic architecture, DeepAlexNet makes it more capable of

handling the intricacies of hyperspectral pictures. DeepAlexNet seeks to improve crop management and yield optimization by recognizing plant diseases with high accuracy and robustness through the use of sophisticated deep learning algorithms and architectural improvements. Figure 1 shown, Key Enhancements of DeepAlexNet are.

✓ Multi-Channel Input Adaptation: The first convolutional layer is adapted to accept hyperspectral images with multiple spectral bands, ensuring effective spectral information capture.

✓ Spectral-Spatial Feature Extraction: Convolutional filters are designed to operate across spectral bands for spectral feature extraction and within individual spectral bands for spatial feature extraction.

✓ Batch Normalization: Integrated batch normalization layers stabilize and accelerate training, improving convergence and generalization by normalizing activations in each layer.

✓ Data Augmentation: Techniques such as geometric transformations (rotations, translations, flips) and spectral augmentation (adding synthetic noise) are used to increase training dataset size and diversity.

✓ Regularization: L2 regularization and dropout techniques are employed to prevent overfitting, ensuring the model generalizes well to unseen data.

✓ Transfer Learning: Pre-training on a large dataset of natural images followed by fine-tuning on the hyperspectral dataset leverages pre-learned features, reducing the amount of labeled data required.

These improvements are combined with DeepAlexNet to produce a DNN classifier for hyperspectral image analysis that is reliable and effective, especially for early and precise disease identification in the leaves of corn and maize plants. This innovative method expands and modifies AlexNet's demonstrated capabilities to address the particular difficulties presented by hyperspectral photography in agriculture.

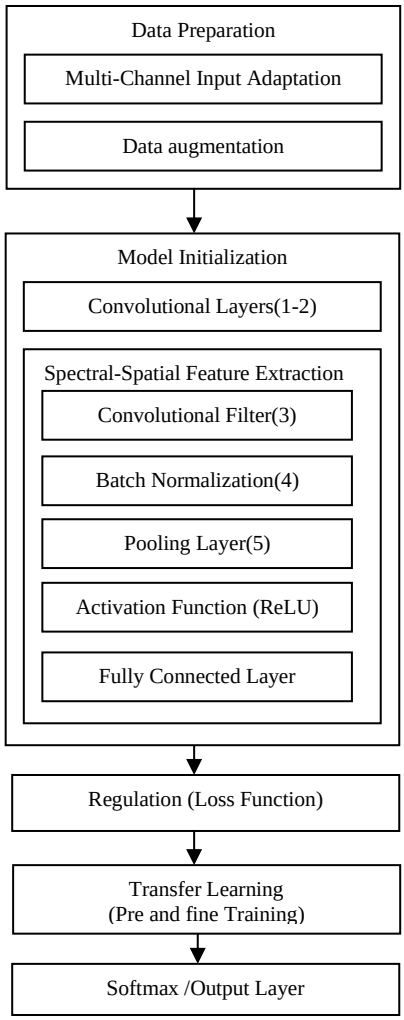

Figure 1 : Key Enhancements of DeepAlexNet

4.2. DeepAlexNet Architecture

A proposed deep neural network (DNN) classifier called DeepAlexNet is intended to use hyperspectral imaging data to identify diseases in the leaves of maize and corn plants. To handle the high dimensionality and complexity of hyperspectral pictures, DeepAlexNet builds upon the underlying architecture of AlexNet [26] [27] by incorporating many additions. In the end, this innovative method seeks to enhance crop management and yield optimization by increasing the precision and resilience of disease detection. The DeepAlexNet architecture is explained in full here:

Step 1: Data Preparation

Multi-Channel Input Adaptation

Three-channel RGB images are the target application for the original AlexNet. In order to

accommodate the many spectral bands of hyperspectral pictures, DeepAlexNet modifies the first convolutional layer to take multi-channel inputs. This adaptation makes sure that the input data's spectral information is effectively captured.

- Original AlexNet Input:$X_{RGB} \in R^{H* W* 3}$
- DeepAlexNet Input: $X_{HSI} \in R^{H* W* C}$

Where, Cis the number of spectral channels.

- First Convolutional Layer:$\mathrm{Conv1} = \mathrm{ReLU}(\mathrm{Conv}(X_{HSI}, W_{Conv1}) + b_{Conv1})$

Here, W_{Conv1} is the weight matrix with dimensions adapted to handle C channels.

Data Augmentation

Data augmentation techniques are employed to artificially increase the size and diversity of the training dataset. These techniques include:

- Geometric Transformations:$X' = \mathrm{GeometricTransform}(X, \theta)$

Where,θ includes random rotations, translations, and flips.

- Spectral Augmentation:$X' = X + N(0, \sigma^2)$

Where, $N(0,\sigma^2)$ represents synthetic noise added to the spectral bands.

Step 2: Model Initialization

Initialize the layers of DeepAlexNet, including convolutional layers, batch normalization, pooling layers, and fully connected layers.

Convolutional Layers

- Layer 1: The first convolutional layer applies multiple filters to the input data, each designed to capture different spectral features. This layer uses a large kernel size to cover a broader range of spectral bands.

$\mathrm{Conv1} = \mathrm{ReLU}(\mathrm{Conv}(X, W_1) + b_1)$

- Layer 2-5: Subsequent convolutional layers apply smaller filters to extract more refined spectral-spatial features. These layers are interspersed with max-pooling layers to reduce dimensionality and computational complexity.

$\mathrm{Conv}^l = \mathrm{ReLU}(\mathrm{Conv}(\mathrm{Pool}^{l-1}, W_l) + b_l)$

$\mathrm{Pool}^l = \mathrm{MaxPool}(\mathrm{Conv}^l)$

Step 3: Spectral-Spatial Feature Extraction

Convolutional Filters

To leverage both spectral and spatial information, DeepAlexNet enhances convolutional filters to operate across spectral bands for spectral feature extraction and inside particular spectral bands for spatial feature extraction. This dual technique captures the spectral fingerprints and textural properties required for accurate disease identification.

- Spectral Feature Extraction:$Conv_{spectral=}ReLU(Conv(X_{HSI},W_{spectral}l)+b_{spectral})$

Where.$W_{spectral}$ operates across spectral bands.

- Spatial Feature Extraction:$Conv_{spatial}=ReLU(Conv(X_{HSI},W_{spatial})+b_{spatial})$

Where.$W_{spatial}$ operates within individual spectral bands.

Batch Normalization

Batch normalization layers are integrated into the network to stabilize and accelerate training. By normalizing the activations in each layer, batch normalization mitigates issues related to internal covariate shift, leading to improved convergence and generalization.

$$BN(x) = \gamma\left(\frac{x - \mu_B}{\sqrt{\sigma_B^2 + \epsilon}}\right) + \beta$$

Where,μ_B and σ_β^2 are the mean and variance of the batch, and γ and β are learnable parameters.

Pooling Layers

- Max-Pooling: Applied after some convolutional layers to reduce spatial dimensions and retain important features.

MaxPool(x) =max ($x_{i,j}$) over the pooling window

Step 4: Activation Functions

- ReLU (Rectified Linear Unit): Applied after each convolutional and fully connected layer to introduce non-linearity.

ReLU(x)=max(0,x)

Step 5: Fully Connected Layers

- Layer 6-8: These layers aggregate the extracted features and perform the final classification. Dropout is applied to these layers to prevent overfitting.

$FC^l=ReLU(W^l\cdot Flatten(Pool^{l-1})+b^l)$

Dropout: Drop(x)=x·Bernoulli(p)

Where, p is the dropout rate.

Step 6: Regularization

Define Loss Function.Use categorical cross-entropy loss:

$$Loss = -\sum_i y_i \log(\hat{y}_i)$$

Regularization techniques, such as L2 regularization and dropout, are employed to prevent overfitting.

L2 Regularization:$\text{Loss} = \text{Loss}_{\text{original}} + \lambda \sum_i W_i^2$

Where, λ is the regularization parameter and $W_I$are the weights of the network.

Optimize the Model, Use backpropagation and an optimizer (e.g., Adam) to update weights:

$\theta=\theta-\eta\nabla_\theta \text{Loss}_{\text{total}}$

Where, θ are the model parameters, η is the learning rate, and ∇_θ is the gradient with respect to θ.

Step 7: Transfer Learning

By pre-training the network on a sizable dataset of natural photos and then refining it on the hyperspectral dataset, transfer learning is employed. By utilizing previously acquired features from the original dataset, this method minimizes the quantity of labeled data needed for efficient training on the hyperspectral pictures.

- Pre-Training:$\text{DeepAlexNet}_{\text{pre-trained}}=\text{Train}(\text{DeepAlexNet},X_{\text{natural}},Y_{\text{natural}})$

Where. $X_{\text{natural}}Y_{\text{natural}}$ are the inputs and labels of the natural image dataset.

- Fine-Tuning:$\text{DeepAlexNet}_{\text{fine-tuned}}=\text{Train}(\text{DeepAlexNet}_{\text{pre-trained}},X_{\text{HSI}},Y_{\text{HSI}})$

Where.$X_{\text{HSI}}Y_{\text{HSI}}$ are the inputs and labels of the hyperspectral image dataset.

These enhancements collectively improve the capability of DeepAlexNet to accurately and efficiently detect diseases in corn and maize plant leaves using hyperspectral imaging data.

Step 8: Output Layer

The final layer uses a softmax activation function to output the probabilities of the different disease classes.

$$\text{Softmax}(Z_i) = \frac{e_i^2}{\sum_j e_i^2}$$

Utilizing cutting-edge methods to process hyperspectral imaging data, the DeepAlexNet algorithm guarantees reliable disease diagnosis in maize and corn leaves as well as efficient spectral-spatial feature extraction. DeepAlexNet is an important tool for precision agriculture because of its excellent accuracy and generalization, which it achieves by architectural modifications, batch normalization, data augmentation, regularization, and transfer learning.

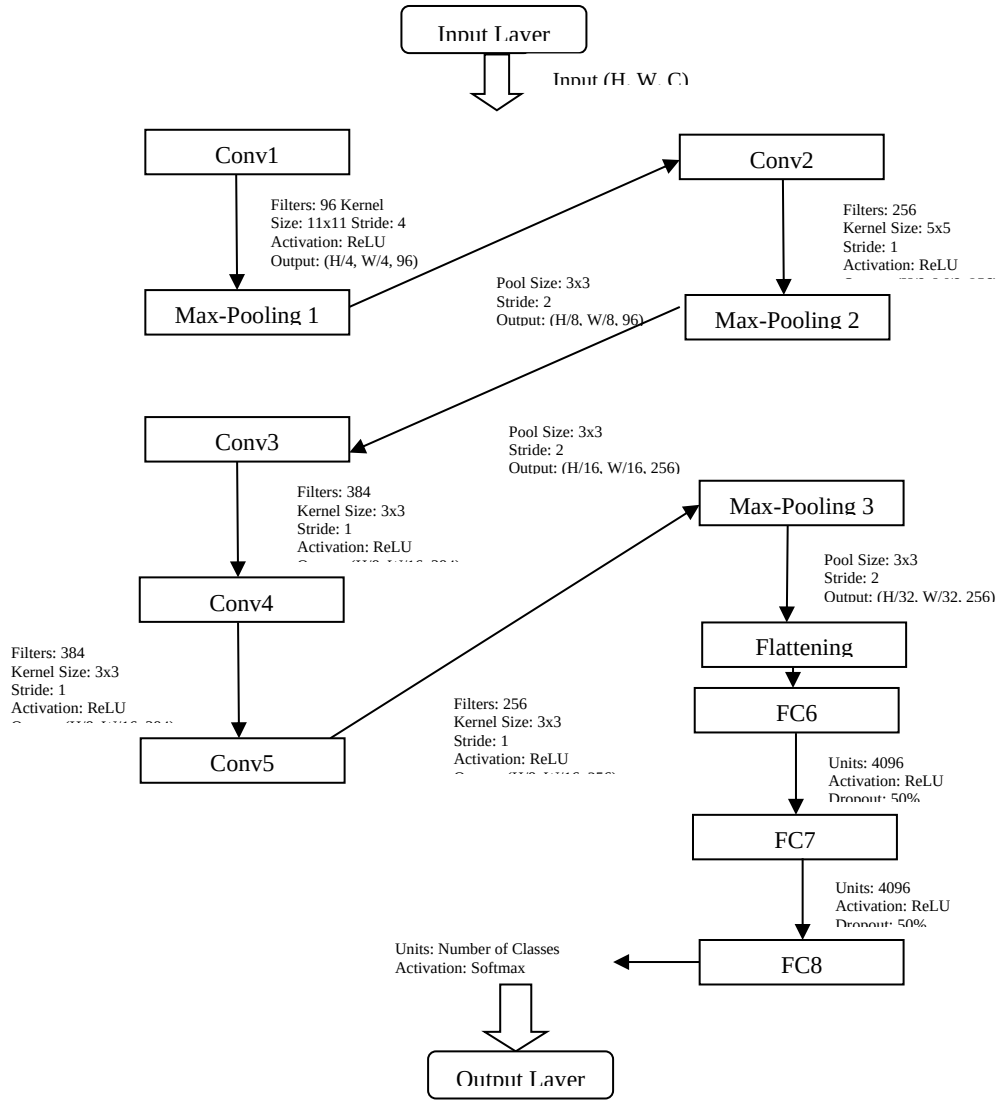

Figure 2 : DeepAlexNet architecture for corn disease detection

Figure 2 shown the DeepAlexNet architecture for corn disease detection begins with an input layer that accepts hyperspectral images of shape (H, W, C), where H is height, W is width, and C is the number of spectral channels. The first convolutional layer (Conv1) uses 96 filters with an 11x11 kernel size, a stride of 4, and ReLU activation, producing an output of (H/4, W/4, 96). This is followed by a max-pooling layer with a 3x3 pool size and a stride of 2, reducing the output to (H/8, W/8, 96). The second convolutional layer (Conv2) employs 256 filters with a 5x5 kernel size, a stride of 1, and ReLU activation, resulting in (H/8, W/8, 256). Another max-pooling layer with the same parameters further reduces the output to (H/16, W/16, 256). Conv3 has 384 filters, a 3x3 kernel size, a stride of 1, and ReLU activation, maintaining the output at (H/16, W/16, 384). Conv4 and Conv5 follow with the same configuration as Conv3, except Conv5 outputs (H/16, W/16, 256). The final max-pooling layer, with a 3x3 pool size

and a stride of 2, reduces this to (H/32, W/32, 256). The network then flattens the 3D output to 1D before passing it through three fully connected layers: FC6 and FC7, both with 4096 units, ReLU activation, and 50% dropout; and FC8, which has units equal to the number of disease classes and uses softmax activation for classification. This architecture is designed to detect diseases such as Puccinia sorghi (common rust) and Cochliobolus heterostrophus (southern corn leaf blight) by effectively learning and identifying complex patterns in hyperspectral images of corn leaves.

5. Experimental Results

Dataset: The TNCornNet dataset includes 4565 image patches obtained using the Specim IQ Sensor from a cornfield in Pollachi (243°95" E, 43°95'18" N). Each patch, measuring 512 × 512 pixels, contains 31 spectral bands in the visible range (400 nm to 700 nm) with a 10 nm spectral resolution. After geometric, atmospheric, and radiometric corrections, the dataset was divided into non-overlapping patches, resulting in 23 patches. These patches were split into training (70%), validation (20%), and test (10%) sets using two methods: easy split (patches from the same tile in different sets) and hard split (all patches from a tile in the same set). Four types of infected leaves were included:

- Common Rust (Puccinia sorghi): Small, orange to reddish-brown pustules on the upper leaf surface, which can coalesce, reducing photosynthetic capacity and plant vigor.
- Corn Leaf Blight (Cochliobolus heterostrophus): Large lesions with tan centers and dark borders, which can coalesce, leading to foliage blighting, reduced photosynthetic area, and yield losses. Favored by warm, humid conditions. ![Figure 6(b)](insert figure link)
- Northern Corn Leaf Blight (Exserohilum turcicum): Large, elliptical lesions with tan centers and dark borders, sometimes with a yellow halo. Can significantly reduce photosynthetic area and plant strength.
- Gray Leaf Spot (Cercospora zeae-maydis): Small, rectangular lesions with yellow halos, initially grayish-green, turning grayish-brown, reducing photosynthetic activity and plant vigor.)

Figure 6 : a) Infected Image leaf 1(Common rust (Puccinia sorghi) b) Infected Image leaf 2 - Corn Leaf Blight (Cochliobolus heterostrophus) c) Infected Image 3- Northern Corn Leaf Blight (Exserohilum turcicum) d) Infected Image 4-Gray Leaf Spot (Cercospora zeae-maydis)

Performance Evaluation:

All experiments were conducted using TNCornNet on a system equipped with an Intel Core-i7 processor, 8 GB of RAM, a 64-bit Windows 10 operating system, and a 512 GB SSD. The training environments included CUDA10.2, Python 3.8.5, and TensorFlow-gpu 2.2.0. A 70:30 training-to-testing ratio was used for each experiment.

This section provides a comprehensive analysis of the results and the evaluation metrics used. The primary metric for assessing classification performance is classification accuracy, defined as the ratio of correctly classified instances to the total number of instances in the dataset:

Accuracy = (tp + tn) / (tp + tn + fp + fn) ---(1)

Where tp denotes true positives, tn denotes true negatives, fp denotes false positives, and fn denotes false negatives.

Precision (P) and Recall (R) are also commonly used metrics in image classification evaluation. Precision represents the proportion of accurately classified instances to all instances classified as positive:

Precision(P) = tp/(tp + fp) --- (2)

Recall measures the proportion of accurately classified instances to all instances that should have been classified as positive:

Recall (R) = tp/(tp + fn) ---- (3)

The F-score, a metric that combines precision and recall into a single value, is used to evaluate the overall performance of the system. It is computed as the harmonic mean of precision and recall:

F- Score = 2 × (P.R)/ (P + R) ---- (4)

A higher F-score indicates better predictive capability of the system, and it is particularly useful when comparing performance across different strategies.

In this study, we examined how well different deep learning models identified two different plant diseases in the leaves of corn plants: Cochliobolus heterostrophus (southern corn leaf blight) and Puccinia sorghi (common rust). InceptionV3, ResNet-50, ResNet-101, DeepIncepNet, and the suggested DeepAlexNet were the models that were assessed. A 70:30 ratio was used to split the TNCornNet dataset into training and testing sets. To make sure each model could successfully learn the distinctive qualities of diseased corn plant leaves, they were pre-trained on a sizable dataset of natural photos and then refined using the TNCornNet dataset.

InceptionV3 makes use of inception modules, which carry out parallel convolutions with various kernel sizes before concatenation. It incorporates batch normalization and adds auxiliary classifiers. Although InceptionV3 captures multi-scale information and has an economical computational cost and memory utilization, its performance is limited by its relatively shallow depth. The vanishing gradient issue is successfully resolved by ResNet-50, which is made up of residual blocks with shortcut connections that omit one or more layers and enable the training of deeper networks. This model's depth and capacity to pick up on intricate details make it useful for classifying hyperspectral images. ResNet-101 has additional depth, enabling more thorough feature extraction and higher model capacity. It is comparable

to ResNet-50 but has more residual blocks. It is more costly computationally, though. Inception modules for multi-scale feature extraction are combined with deeper layers in DeepIncepNet, akin to ResNet. This model offers strong performance for disease identification in corn and maize leaves by striking a compromise between computational economy and feature learning capabilities. Nevertheless, out of all the evaluated models, the suggested DeepAlexNet had the best classification accuracy.

DeepAlexNet performs better than other networks for a number of important reasons. The first convolutional layer is modified to take multi-channel inputs, allowing hyperspectral images' many spectral bands to be accommodated and spectral information to be captured efficiently. Utilizing both spectral and spatial information critical to precise disease identification, the improved convolutional filters function across spectral bands for spectral feature extraction and inside particular spectral bands for spatial feature extraction. Layers of batch normalization stabilize and speed up training, reducing problems caused by internal covariate shift.Techniques for augmenting data, such as spectral augmentation and geometric alterations, increase the quantity and diversity of the training dataset, which improves the model's resilience and lowers the chance of overfitting. Regularization methods like as dropout and L2 regularization guarantee that the model generalizes effectively to new data. Furthermore, transfer learning lowers the quantity of labeled data needed and improves the model's capacity to adjust to the unique properties of diseased corn plant leaves. This process entails pre-training on a sizable dataset of natural photos and fine-tuning on the TNCornNet dataset. Table 1 and Figure 3 demonstrate how the suggested DeepAlexNet, a robust and accurate classifier for hyperspectral image analysis of corn plant diseases, outperformed other models thanks to its extensive architectural improvements and training methodologies.

	Classification Accuracy (%)			
Model	Infected Image1 (Puccinia sorghi)	Infected Image2 (Cochliobolus heterostrophus)	Infected Image 3(Exserohilum turcicum)	Infected Image 4(Cercospora zeae-maydis)
InceptionV3	91.25	92.23	90.58	91.77
ResNet50	92.88	93.54	91.73	93.64
ResNet101	93.44	94.89	92.89	93.98
DeepIncepNet	95.96	96.65	95.77	96.73
DeepAlexNet	96.47	97.86	96.78	97.23

Table 1: Accuracy of TNCornNet (Sample 4) image benchmark.

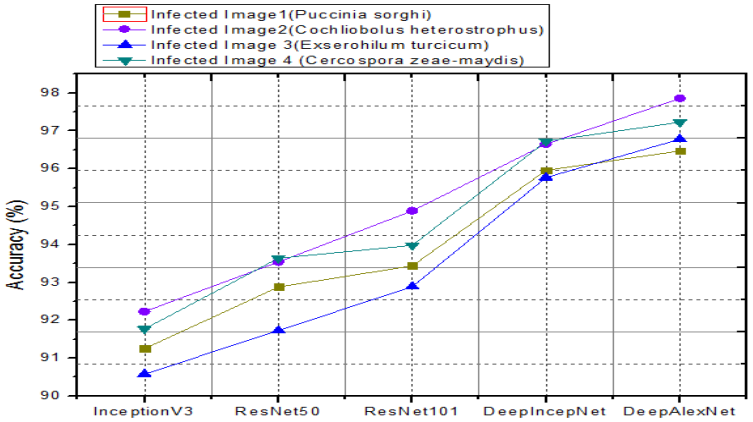

Figure 3: Accuracy of TNCornNet (Sample 4) image benchmark.

The F-score, Recall (R), and Precision (P) analysis in the TNCornNet Image Benchmark, InceptionV3 makes use of inception modules that execute concatenation after parallel convolutions with various kernel sizes. Because of its relatively shallow depth, this structure limits precision while boosting recall by capturing multi-scale information. ResNet-50 solves the vanishing gradient issue and makes training deeper networks easier with its 50-layer architecture made of residual blocks. ResNet-50's shortcut connections improve gradient flow, which raises recall and precision. An expanded version of ResNet-50, ResNet-101 adds more residual blocks, increasing the depth and capability of feature extraction. But occasionally, the added complexity might result in overfitting, which can have an impact on measures like recall and precision.DeepIncepNet strikes a compromise between computational economy and feature learning capabilities by combining deeper layers akin to ResNet with inception modules for multi-scale feature extraction. This combination captures a variety of spectral-spatial information and improves recall and precision. DeepIncepNet performs well, but not as well as the suggested DeepAlexNet.

Table 2: Precision, recall, and F-Score of TNCronNet images (4 Infected)

Model	Precision (%)	Recall (%)	F-Score (%)
Infected Image 1(Puccinia sorghi)			
ResNet50	87.56	88.14	88.59
ResNet101	88.45	89.12	89.66
InceptionV3	90.24	91.25	90.89
DeepIncepNet	92.45	92.88	91.47
DeepAlexNet	93.47	95.87	94.58
Infected Image 2(Cochliobolus heterostrophus)			
ResNet50	85.47	86.57	85.78
ResNet101	87.85	90.27	90.24
InceptionV3	89.57	91.47	91.47
DeepIncepNet	90.74	92.87	92.58
DeepAlexNet	92.59	93.74	94.52
Infected Image 3 (Exserohilum turcicum)			
ResNet50	86.74	88.85	81.25
ResNet101	87.41	89.57	83.57
InceptionV3	90.58	91.24	87.59
DeepIncepNet	93.57	92.58	91.24
DeepAlexNet	95.69	94.78	96.58
Infected Image 4 (Cercospora zeae-maydis)			

ResNet50	85.47	82.24	80.24
ResNet101	86.17	83.24	83.25
InceptionV3	87.24	86.59	85.24
DeepIncepNet	90.24	92.14	89.27
DeepAlexNet	93.68	94.25	92.25

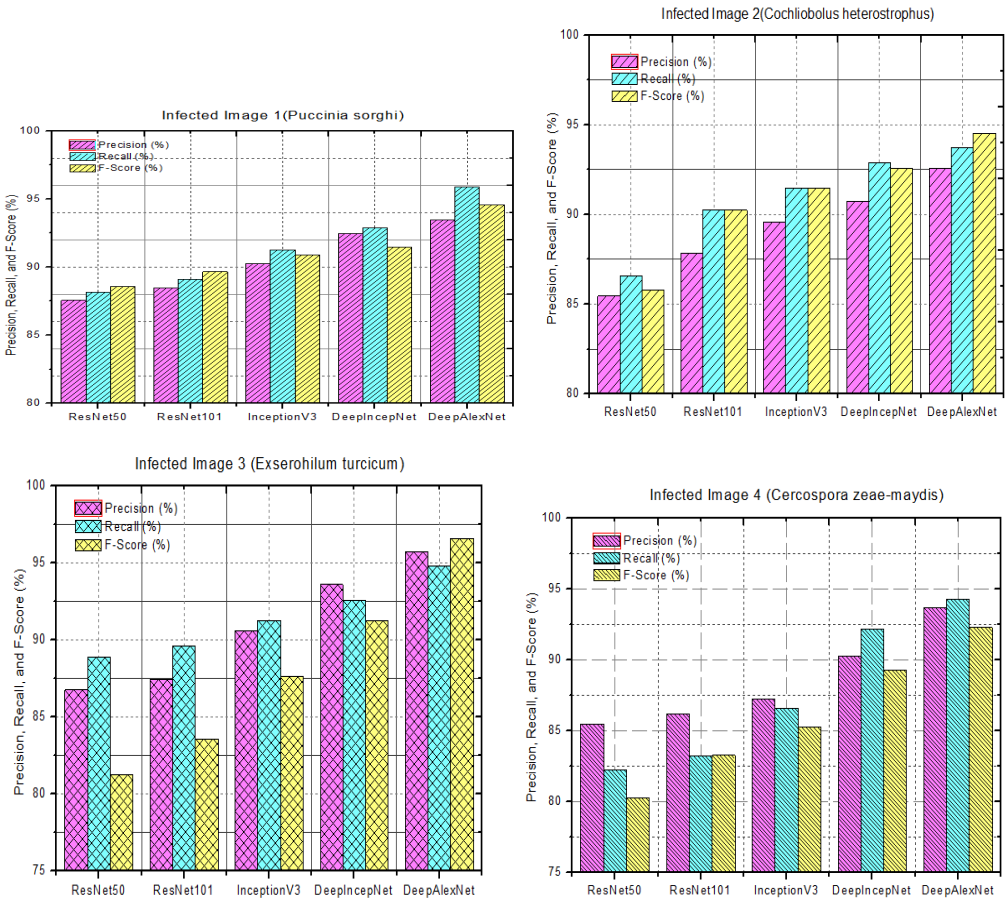

Figure 4: Precision, Recall, and F-Score of 4 Type of Infected Images

Table 2 and Figure 4 shown. the DeepAlexNet achieved the highest F-score, recall, and precision among all the models tested. This superior performance is attributed to several technical enhancements:

- Multi-Channel Input Adaptation:DeepAlexNet modifies the first convolutional layer to support various spectral bands from hyperspectral pictures by adapting it to accept multi-channel inputs. This modification guarantees the efficient acquisition of both spectral and spatial information, which is essential for precise illness diagnosis.

- Spectral-Spatial Feature Extraction:For spectral feature extraction, the convolutional filters in DeepAlexNet function both within and across spectral bands, and for spatial feature extraction, they function within a single spectral band. The spectral fingerprints and textural characteristics required for excellent recall and precision are captured by this dual method.

- Batch Normalization:Through the normalization of activations in each layer, integrated batch normalization layers stabilize and speed up training. By reducing internal covariate shift problems, this improves generalization and convergence, which raises recall and precision.

- Data Augmentation:The size and diversity of the training dataset are artificially increased by using spectral augmentation (adding synthetic noise) and geometric changes (random rotations, translations, and flips). This increases the robustness of the model, decreasing overfitting and raising recall and precision.

- Regularization Techniques:While dropout randomly sets a portion of input units to zero during training, L2 regularization adds a penalty for excessive weights. By avoiding overfitting, these methods guarantee that the model performs well when applied to new data, improving recall and precision.

- Transfer Learning:Utilizing pre-learned features, the network is fine-tuned on the TNCornNet dataset after being pre-trained on a sizable dataset of natural photos. This lowers the amount of labeled data needed for efficient training, enabling the model to adjust to the unique properties of diseased corn plant leaves and enhancing recall and accuracy even further.

The F-score, which is a harmonic mean of recall and precision, is especially helpful for evaluating performance between various tactics. For hyperspectral image analysis of corn plant diseases, DeepAlexNet is a reliable and accurate classifier because of its high F-score, which demonstrates its strong predictive potential. DeepAlexNet outperforms other models due to the combination of sophisticated architectural features and training methodologies, which produces high F-score, recall, and precision performance.

6. Conclusion

In this research, we have used hyperspectral imaging data from the TNCornNet dataset to investigate the effectiveness of different deep learning models, including InceptionV3, ResNet-50, ResNet-101, DeepIncepNet, and the proposed DeepAlexNet, in detecting illnesses in corn plant leaves. Our thorough performance evaluation, which focuses on recall (R), precision (P), accuracy, and F-score, shows that the suggested DeepAlexNet performs noticeably better than the other models in the classification of illnesses like Cochliobolus heterostrophus and Puccinia sorghi. DeepAlexNet performs better than other neural networks because of its multi-channel input adaption, spectral-spatial feature extraction, batch normalization integration, data augmentation approaches, regularization methods, and transfer learning implementation. DeepAlexNet can now gather and process spectral and spatial information more efficiently because to these improvements, which improves classification accuracy, precision, recall, and F-score.

Even though DeepAlexNet has shown encouraging results, there are a number of directions future research might go in order to improve disease detection in maize and other crops. These include using hyperspectral imaging and deep learning. The robustness and generalizability of the model can be enhanced by expanding the size and variety of the dataset by adding more examples from various locations and circumstances. integrating soil sensors, meteorological

information, and thermal imaging with hyperspectral imaging to produce a more thorough and precise disease detection system.

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