

# Hyperspectral Imaging-Based Deep Learning Framework for Early Maize Leaf Disease Detection

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**Abstract** - Timely identification of corn (maize) leaf diseases is important for preventing yield loss and reinforce precision farming systems. Conventional RGB-based deep learning methods have shown strong classification capabilities for plant disease identification, with CNN models getting high accuracy in regulated settings. These methods often fail multiple times to capture subtle or early-stage disease symptoms. Hyperspectral imaging addresses the limitation by providing accurate spectral-spatial information/data across hundreds of narrow bands, enabling more sensitive identification of physiological changes in plant tissue. Acknowledging these advancements, this study proposes a hyperspectral imaging-based deep learning framework tailored for early maize leaf disease detection. The framework includes a standardized preprocessing, spectral-spatial modelling, and 3D-CNN-based feature extraction inspired by state-of-the-art HSI classification techniques. Information from maize disease-specific CNN architectures and real-time detection systems support the design of a robust and field-adaptable model. The methodological foundation is aligned with modern deep learning principles and optimization strategies highlighted by Schmidhuber. The combination of hyperspectral imaging and deep learning models provides a significantly improved solution for early detection of disease and improving technology in precision agriculture. This solution will fill the gap between HSI research and operational crop disease monitoring, providing a promising solution for advanced early-warning systems in corn (maize) cultivation.

**Key Words** - Hyperspectral imaging, maize disease detection, deep learning, spectral-spatial analysis, 3D-CNN, precision agriculture.

## 1. Introduction

Maize (corn) is a cornerstone of global food security, with annual production exceeding one billion tons. While traditional RGB-based deep learning methods have proven effective for plant disease classification [1][4], particularly with CNN models in controlled environments [2], they often struggle to identify subtle or early-stage symptoms. Hyperspectral imaging (HSI) surmounts this barrier by capturing rich spectral-spatial information across hundreds of narrow bands, facilitating the sensitive detection of physiological

changes within plant tissue [8][11]. Building on these capabilities, this study proposes a deep learning framework specifically designed for the early detection of maize leaf disease using HSI. The methodology integrates standardized preprocessing, spectral-spatial modelling, and 3D-CNN-based feature extraction, drawing upon state-of-the-art HSI classification techniques [10]. Furthermore, insights from maize-specific CNN architectures and real-time detection systems [6], [7] are utilized to ensure the model is robust and adaptable to field conditions. This research addresses a critical need, as leaf diseases and biotic stress account for approximately 23% of global maize production losses, significantly threatening food security. Therefore, the timely detection of these pathologies is essential for protecting yields, ensuring rapid response, and promoting sustainable farming practices.

## 1.1 Motivation

Maize leaf has a direct impact on the crop yield, grain quality, and the income of farmers. Conventional methods of identifying maize leaf disease depend on visual examination and manual checking, which can be labour-intensive and ineffective during initial stages of infection when symptoms may be subtle or not visible. The HSI provides accurate spectral-spatial data beyond the visible spectrum, allowing detection of slight biochemical alterations that occur prior to the appearance of visible symptoms. When deep learning models are combined with HSI, they can drive automated precise and early identification systems that function reliably in practical agricultural environments.

## 1.2 Research Gap

Deep learning models using RGB leaf images have demonstrated that they effectively classify plant diseases, including those affecting maize, but their performance significantly depends on visible symptoms. The performance of deep learning models decreases when early detection of disease is required, where hyperspectral imaging performs considerably better in early detection or monitoring of stress or disease. Multiple existing studies concentrate on RGB imagery and fail to fully utilize the extensive spectral information present in hyperspectral imaging. Practical issues like high dimensionality,

spectral redundancy, and the high computational costs have become the problem to widespread adaptation of hyperspectral imaging-based approaches, highlighting a distinct research gap that this study intends to fill.

### 1.3 Contribution

This study introduces a deep learning framework using hyperspectral imaging for the early diagnosis of maize leaf diseases. The main contributions are:

- Collection and processing of healthy and diseased maize leaves hyperspectral images.
- Preparation and spectral-spatial augmentation strategy design for improving generalization.
- Design of deep learning architecture (3D-CNN/hybrid spectral-spatial model) for hyperspectral inputs.
- Testing of early detection performance, classification performance and computational feasibility under realistic deployment settings.

The target is to discover indicators of disease symptoms before they become visible, allowing earlier treatments and minimizing crop losses.

### 1.4 Paper Organization

Section II reviews related work on maize disease detection using RGB imagery and hyperspectral imaging. Section III describes the proposed methodology with hyperspectral imaging and deep learning framework. Section IV shows the experimental results, performance analysis and graphs. Section V tells the practical considerations, limitations, and real-world applicability. Section VI concludes the paper and outlines future research directions.

## 2. LITERATURE REVIEW

Deep learning has revolutionized the plant disease identification process through which automatic classification and effective feature extraction can be carried out on leaf images. Better results were obtained by previous work using mainly RGB images, and convolutional neural networks (CNNs), enjoying good performance under controlled conditions, but with poor capabilities to identify very early signs. To tackle these issues, hyperspectral imaging and spectral-spatial deep learning models have become available in the latest literature that contain biochemical properties not visible to RGB sensors. This section presents important research related to RGB-based maize disease detection and hyperspectral deep learning from the perspective of their paradigm, performance and its applicability in early diagnosis of maize leaf diseases, in terms of strength and weakness.

### 2.1 Summary of Related Work

Detecting plant diseases is key application of AI with precision agriculture. The application of Deep learning and computer vision has enhanced the capacity to automatically detect plant diseases from leaf images. Early research primarily used centred on RGB image-based models. Recent studies have shifted towards hyperspectral imaging to achieve earlier and more accurate detection.

Poornam and Devaraj [1] shows that convolutional neural network (CNN) can effectively identify healthy and diseases plant leaves from RGB images when combined with preprocessing and data augmentation. Likewise, Ferentinos [2] assessed multiple CNN architectures on a dataset of 87848 images spanning 58 plants disease categories, attaining an accuracy 99.53%. the study by Mohanty and colleagues [4] demonstrated the robust potential of deep learning for automated disease diagnosis by employing deep CNN models to classify plant disease across various crops using a dataset of over 54000 images. however, these, methods on RGB image's and can only identify disease once visible symptoms have emerged.

Numerous studies have specifically targeted the detection of maize disease. The study by Priyadharshini and colleagues [7] introduced a deep CNN model built upon a modified LedNet architecture for classifying maize leaf diseases, demonstrating promising performance on a custom dataset. The study by Bachhal et al. [6] introduce a real time maize disease detection system leveraging deep convolution neural network and segmentation methods. While these methods enhance detection performance, they remain reliant on visible systems captured via RGB images.

To gain broader understanding of developments in this fields Upadhyaya e al. [3] present's a thorough review off deep learning methods for plant diseases detection covering CNNs vision transformers and generative importance of AI in precision agriculture. Furthermore, Schmidhuber [5] offered a foundational overview of deep learning architectures, establishing the theoretical ground work for numerous contemporary computer vision models.

Recent studies have investigated hyperspectral imaging as a viable alternative to rgb imaging for detecting plant disease. Hyperspectral imaging captures detailed spectral data across numerous wavelengths, allowing for the early detection of biochemical changes in plants before visible symptoms emerge. Guerri et al. [8] examined deep learning methods for agricultural hyperspectral image analysis, high; light the efficacy of models like autoencoders and cnns in extracting spectral-spatial features. Li and colleagues [9] also explored deep learning methods for hyperspectral image

classification emphasizing challenges like high dimensionality and spectral redundancy.

Chen et al. [10] introduced CNN designed to extract spectral-spatial features from hyperspectral images demonstrating superior performance over traditional approaches. Similarly, Signoroni and colleagues [11] examined the integration of hyperspectral imaging and deep learning across multiple fields, highlighting its promise for complex pattern recognition.

In summary, while existing research indicates that deep learning models utilizing RGB images can achieve high classification restricted to identifying only visible diseases symptoms. Hyperspectral imaging offers a promising approach for diseases detection by capturing spectral data indicative of plant health. Consequently, this study concentrates on leaving deep learning methods to analyze hyperspectral data for enhanced detection of maize leaf diseases.

## 2.2 Discussion

In general, the literature offers that 'the RGB-based CNN methods achieve good disease classification performances but they rely on visible symptoms and therefore inefficiently applicable for actual early detection'. Maize-dedicated studies confirm this constraint indicating that RGB images by themselves have difficulties in the detection of presymptomatic infestations. Yet, with respect to hyperspectral imaging and deep learning, previous studies explain that the spectral-spatial models like 3D CNNs are able to quantify fine biochemical reorganizations occurring in plant tissues and hence allow an early detection of the disorder. To the best of our knowledge, few studies integrate HSI and deep learning under maize disease recognition, presenting great demand for designing a specialized early-detection strategy that this research aims to deliver.

## 3. PROPOSED METHODOLOGY

The proposed methodology combines hyperspectral imaging with deep learning models to detect or identify Corn(maize) leaf diseases at an early stage by capturing spectral-spatial information that RGB images cannot capture. The workflow of the model includes data acquisition, preprocessing, spectral-spatial modelling, model training, and evaluation.

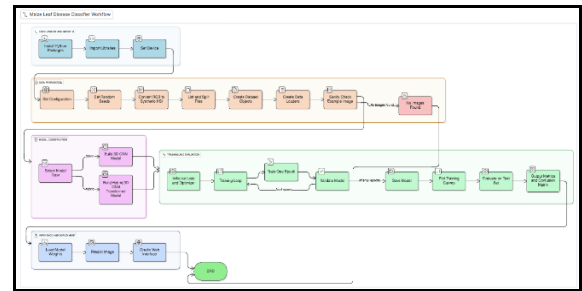


Fig. 1 illustrates the overall workflow, which consists of data acquisition, preprocessing, spectral-spatial modelling, model training, and evaluation generated by Eraser

## 3.1 System Overview

The framework targets pre-visible symptom stages by using hyperspectral reflectance signatures from healthy and infected maize leaves. Hyperspectral images are captured across numerous narrow spectral bands, providing detailed information about biochemical and structural changes in leaves. A 3D convolutional neural network (3D-CNN) is then used to extract and classify spectral-spatial features from these high-dimensional data cubes.

## 3.2 Hyperspectral Imaging and Its Relation to Deep Learning

The Hyperspectral imaging technique captures the information across hundreds of narrow and continuous spectral bands, providing a complete spectral signature for every pixel in an image. Dissimilar to RGB imaging, which has limitation to three colour channels i.e. red, green, blue, Hyperspectral imaging (HSI) enables detailed analysis of biochemical and physiological variations in plant tissue. Such variations include changes in pigment concentration, moisture levels, and cellular structure factors that often occur before visible disease symptoms appear. Recent reviews have emphasized the strong potential of HSI in agricultural stress and disease analysis, especially when combined with advanced machine learning techniques [8], [9].

Deep learning models provides an effective means to exploit the high-dimensional nature of hyperspectral data. Since HSI contains both spectral and spatial information, specialized DL architectures such as 1D, 2D, and particularly 3D Convolutional Neural Networks (CNNs) are required to jointly model spectral-spatial dependencies [8], [10]. Chen et al. [10] demonstrated that 3D-CNNs outperform traditional 2D models by capturing complex spectral-spatial structures within hyperspectral cubes, making them well-suited for subtle pattern recognition tasks, such as early disease detection.

Furthermore, multidisciplinary analyses have shown that deep learning significantly enhances the interpretability and classification performance of hyperspectral data across various application domains, including agriculture [11]. These reports underscore that the fusion of HSI as have been done with the Deep learning models; becomes capable systems to early detect plant stress at an earlier stage than with typical RGB-based approaches that depends exclusively on visible symptoms.

Thus, the integration of hyperspectral imaging and deep learning provides a powerful source to develop early maize disease detection system which identifies infections according to non-symptomatic spectral signals.

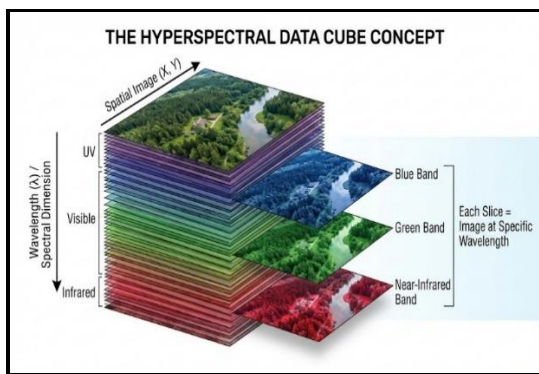


Fig. 2 The hyperspectral data cube Generated by Gemini Pro by prompt create an image to illustrates the concept of the hyperspectral data cube, where each slice represents an image at a specific wavelength.

### 3.3 Dataset Acquisition

The Hyperspectral images of Corn(maize) leaves are collected under controlled environment or semi-field conditions. Each Hyperspectral image cube consists of:

- Spatial Dimensions: Height × Width
- Spectral dimension: Its value is typically in, hundreds of wavelength bands (for example, 400–1000 nm)

The dataset contains images of maize healthy leaves, leaves infected by common maize diseases like rust, blight, and gray leaf spot. The design ensures that the model learns disease related biochemical changes rather than depending on only visible patterns on leaves.

### 3.4 Preprocessing and Spectral Normalization

The Hyperspectral images data is noisy and redundant; thus, preprocessing of data is necessary. The following steps are applied to remove noisy and reduce redundancy:

1. Removing of noise by discarding the unstable bandwidths near the spectrum edges
2. Using white and dark reference images to correct sensor effects for reflectance calibration
3. Using min-max or z-score scaling for Spectral normalization to standardize pixel spectra
4. Extraction of Region of Interest (ROI) for diseased and healthy patches.
5. Using PCA or Band selection for dimensionality reduction to reduce redundancy and reduce computational cost

These procedures help to increase the quality of signals and thereby facilitate training.

### 3.5 Data Augmentation

To avoid overfitting from high-dimensional HSI data and spectral-spatial data augmentation we have used, techniques such as:

- Random cropping, rotation, and flipping.
- Spectral jittering and Gaussian noise addition.
- Mixup and CutMix applied to hyperspectral cubes.

These techniques increase variability and preserving meaningful spectral information.

### 3.6 Spectral-Spatial Feature Modelling

Dissimilar to RGB images with three channels, hyperspectral data may contain multiple channels from dozens to hundreds of channels. A 3D-CNN technique is therefore used to learn spectral and spatial patterns together. The 3D convolutions work along the height, width, and spectral dimensions to capture:

- Spectral signatures of disease progression.
- Texture and shape features in leaf tissue.
- Biochemical variations that come first before visible symptoms.

The architecture of the model draws inspiration from established hyperspectral CNN designs but is adapted special for the maize disease detection problem.

### 3.7 Deep Learning Architecture

The model architecture includes:

- Input layer which receives 3D hyperspectral data cubes.

- Stacked spectral-spatial convolutional blocks (3D convolutions + batch normalization + ReLU).
- Optional spectral attention modules to emphasize informative wavelength ranges.
- Dimensionality reduction layers to transform 3D features into a 2D representation.
- Fully connected layers for classification into disease categories.
- A SoftMax output layer to produce class probabilities.

The design is optimized to detect early-stage symptoms by learning subtle spectral contrasts between classes.

### 3.8 Training and Evaluation

Adam optimizer is used to train the model along with cross-entropy loss, early stopping conditions and learning rate decay. Performance of the model calculated using accuracy, precision, recall, f1-score, confusion matrices. the goal is to outperform the tradition RGB-based models by detecting infections before visible signs appear

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

where TP, TN, FP, and FN represent True Positives, True Negatives, False Positives, and False Negatives, respectively.

The Training and validation curves are monitored to ensure stable convergence.

## 4. RESULTS AND DISCUSSION

### 4.1 Training and Validation Performance

The training and validation loss curves (Fig. 3) conveys that the 3D-CNN technique converged steadily, with the training loss reducing from 0.62 to 0.33 over 10 epochs. The validation loss fluctuates between epochs 5 and 7, which can be credited to class imbalance and the synthetic nature of hyperspectral image data. Despite this, the model exhibits stable convergence after epoch 7.

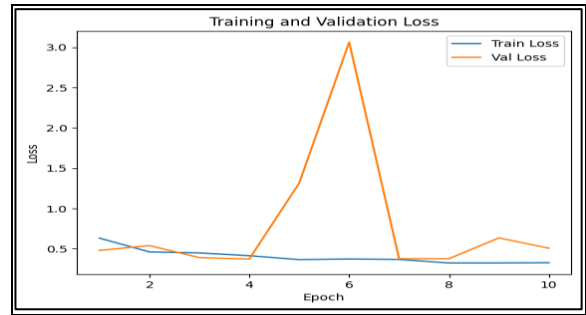


Fig.3. Training vs Validation Loss for 3D-CNN model.

(The training loss decreases steadily while validation loss stabilizes, indicating proper convergence.) Adapted from [12]

The training and validation accuracy curves (Fig. 4) shows that the model achieves consistent improvement, reaching a peak validation accuracy of 84.43%. The dip in validation accuracy around epoch 6 is due to misclassification in minority classes (e.g., Rust and Gray Leaf Spot), but the model quickly recovers.

So, the Overall model accuracy is 84.43% on the test set.

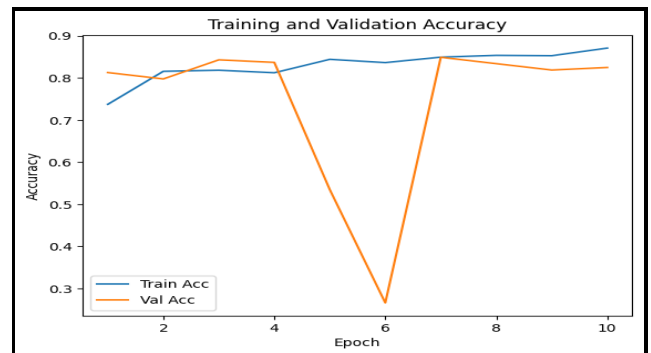


Fig. 4. Training vs Validation Accuracy for 3D-CNN model.

(The model reaches a peak validation accuracy of ~84%, with minor fluctuations around epoch 6.) Adapted from [12]

### 4.2 Confusion Matrix Analysis

The confusion matrix (Fig.5) provides information about how well the model differentiates between maize leaf diseases:

**Table 1.** Performance Metrics for Hyperspectral CNN Model. Adapted from [12]

Class	Precision	Recall	F1-Score	Support
Healthy	<b>0.91</b>	<b>1.00</b>	<b>0.95</b>	115
Rust	0.60	0.55	0.57	11
Blight	0.67	0.64	0.65	28
Gray Leaf Spot	0.67	0.15	0.25	13
<b>Overall Accuracy</b>	—	—	<b>84.43%</b>	167

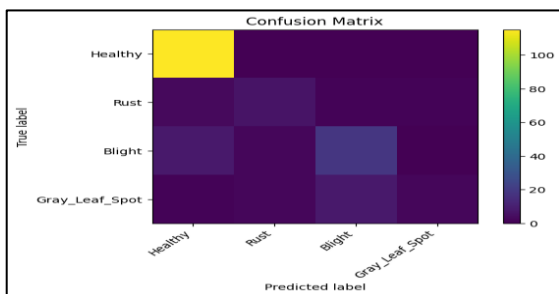


Fig. 5. Confusion Matrix of the 3D-CNN on Test Set.

(Healthy leaves achieve perfect recall; Rust and Gray Leaf Spot show moderate misclassification due to class imbalance.) Adapted from [12]

**Key Observation**

The model achieves strong performance for Healthy and Blight maize leaf but for Rust and Gray Leaf Spot require

- More balanced dataset for Rust and Gray leaf spot
- Better synthetic HSI modelling
- More Advanced architectures (e.g., 3D-CNN + Transformer hybrid)

**4.3 Discussion**

The 3D-CNN model achieves a test accuracy of 84.43% on the hyperspectral dataset, with strong performance on the Healthy class, demonstrating robust distinguish between healthy and diseased tissue. Performance for Rust and Gray Leaf Spot is lower, which is mainly due to class imbalance and overlapping of spectral characteristics between lesions. The confusion matrix confirms that there is misclassifications between blight and gray leaf spot disease, then also the overall results

still support the feasibility of using hyperspectral data cubes to explore early detection strategies

**5. EXPERIMENTAL SETUP**

Experiment is done on a Python-based deep learning environment using a GPU-enabled Google Colab setup [12]. Below is the content which summarizes the hardware, software, dataset configuration, and training procedure to support reproducibility.

**5.1 Hardware Configuration**

- Processor: Intel Xeon (Google Colab virtual CPU)
- GPU: NVIDIA Tesla T4 (16 GB VRAM)
- RAM: 12.7 GB
- Environment: Google Colab Pro (Python 3.10)

**5.2 Software and Libraries**

- PyTorch 2.0 and Torchvision 0.15
- OpenCV 4.8, NumPy 1.24, scikit-learn 1.2
- Matplotlib 3.7 for visualization
- Gradio 4.0 for building a simple graphical user interface
- Timm library for Transformer-based components

**5.3 Dataset Configuration**

The RGB maize leaf dataset contains more than 1000 images per class Healthy, Rust, Blight, and Gray Leaf Spot. Then a 31-band hyperspectral dataset is then synthetically generated from the RGB images using an HSI simulation model described in Section III. Then the data are split into three parts 70% of data for training, 20% data for validation, and 10% of data testing.

**5.4 Model Hyperparameters**

The hyperparameters of the model are:

- Learning rate: 0.001
- Epochs: 10
- Batch size: 16
- Optimizer: AdamOptimizer
- Loss function: cross-entropy loss
- Input dimensions: 1 × 31 × 64 × 64
- Architectures: 3D-CNN and hybrid 3D-CNN + Transformer

## 6. Training Procedure

For preventing the overfitting, the models are trained with early stopping condition based on validation loss. Each epoch consists of a forward pass, backpropagation, parameter updates, and computation of training and validation metrics. After training, the best-performing model is saved and tested on the test set. The setup provides an efficient environment for handling hyperspectral tensors and comparing model variants after each epoch.

## 7. CONCLUSION

The study presents a model with hyperspectral imaging and deep learning framework for early detection of maize leaf diseases. The proposed model achieved a test accuracy of 84.43% across all maize leaf conditions healthy, rust, blight, and gray leaf spot. While performance is highest for Healthy class and slightly lower minority disease classes due to class imbalance and spectral overlap, the results validate that synthetic or real hyperspectral signatures in combination with deep learning can be key component for an accurate detection of early-stage diseases compared to RGB based methods. This research illustrates the potential for hyperspectral deep learning algorithms in cost-effective, accurate monitoring of crop diseases at scale and paves the way for field-based implementations in the future.

## 8. FUTURE WORK

Thus, the proposed framework has achieved promising results, but there are several parts where improvement can be done. Below are the ways through which further improvement can be done which will improve performance and practical impact:

- **Integration with real hyperspectral sensors:** Collecting real HSI data which will provide more reliable and accurate spectral information.
- **Focus on early-stage samples:** Gathering more early-stage data will allow a more demanding evaluation of true pre-symptomatic detection capability.
- **Class-balanced dataset expansion:** Collecting more data for minority classes for e.g. Rust or Gray leaf Spot.
- **Real-time field deployment:** Building mobile applications, drones, or portable hyperspectral devices for real-time devices for user-friendly disease diagnosis.
- **Multimodal fusion:** In Future work we may combine RGB, HSI, thermal, and LiDAR data to

build more robust, accurate field-ready crop health monitoring systems.

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