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Classification Of Wheat Disease Using CNN

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ABSTRACT

Leaf rust, stem rust, and powdery mildew are just a few of plant diseases that may drastically reduce the productivity of wheat, a cereal crop that is crucial on a worldwide scale. In order to intervene quickly and implement sustainable farming techniques, early and precise disease diagnosis is essential. Automated disease classification in wheat utilizing CNN is presented in this paper as a deep learning-based technique. In order to make the model more generalizable, it was preprocessed and enhanced using a dataset of wheat leaf photos that included images of various diseases. Input photos were used to train a bespoke CNN architecture that could learn hierarchical features. Model's strong performance in differentiating amongst infected and healthy wheat samples was shown by its high classification accuracy. In terms of accuracy, recall, and total F1-score, CNN model outperforms conventional machine learning classifiers. With suggested approach, agronomists and farmers may have access to a scalable and effective tool for early disease identification in wheat, which would allow for more precise treatment and less yield loss.

***Index Terms*— Wheat, convolutional neural networks (CNNs), MRI, agronomists, farmer, leaf rust, stem rust, and powdery mildew**

I. INTRODUCTION

Among the many cereal crops grown and eaten across the globe, wheat (Triticum aestivum) ranks high. Wheat keeps people fed as it is a mainstay for around 35% of the world's population. Bread, spaghetti, biscuits, and a host of other foods all make use of it. Therefore, it is crucial to keep wheat yields high. But several biotic stressors, especially plant diseases, may reduce wheat yields. Economic losses and food shortages, particularly in rural countries, may be caused by common wheat diseases such as stripe rust, leaf rust, stem rust, powdery mildew, and septoria tritici blotch. These diseases extensively lower crop output and quality.

Scouting by hand and professional visual assessment of agricultural fields have been the mainstays of disease identification in wheat up until recently. This strategy has a number of disadvantages, yet it is successful to a certain degree. To start, it's not practical for widespread surveillance because of how time-consuming and labor-intensive it is. Secondly, precise diagnosis necessitates specialized expertise, which is not always present in less developed regions or places with limited resources. Third, weariness, subjective judgment, and environmental fluctuation may lead to mistakes in human observation. The development of automated systems for early illness detection and categorization that are rapid, accurate, and capable of overcoming these hurdles is imperative.

The automation of plant disease detection has been made possible by recent breakthroughs in Artificial Intelligence (AI), namely in Deep Learning (DL) and Computer Vision. Without the need for human feature engineers, deep learning algorithms are able to learn intricate patterns and characteristics from massive datasets. When it comes to medical imaging, object identification, and picture categorization, Convolutional Neural Networks (CNNs) stand head and shoulders above the competition. Their capacity to discern visual patterns and spatial hierarchies makes them ideal for detecting signs of plant diseases in leaves.

If we want to train CNNs to classify wheat diseases, we may use a labeled dataset of pictures of wheat leaves, where each picture represents a different illness or a healthy leaf. The CNN is able to accurately differentiate between several disease types by automatically learning discriminative properties such lesion color, shape, texture, and distribution. Additionally, CNN models are perfect for incorporation into mobile or IoT-based apps for in-field diagnostics since they can work in real-time.

The goal of this study is to create a convolutional neural network (CNN) method for disease classification in wheat leaves. A diversified dataset including several wheat leaf diseases was used to train the system. The dataset was trained under variable lighting conditions and backdrops to mimic real-world scenarios. These are the aims of the research:

Find out how well a bespoke CNN model does at identifying and categorizing various wheat illnesses.

It would be instructive to contrast CNN with more conventional ML classifiers like SVM and RF.

Examine how adding and cleaning up data impacts categorization precision.

Determine if the technology can be used to assist farmers and agricultural extension workers in making decisions.

This study's potential impact on smart farming and precision agriculture is its greatest strength. The usage of chemical pesticides is reduced and production losses are minimized when wheat illnesses are detected early and treated promptly. An automated approach for detecting wheat diseases may provide farmers in areas without easy access to agricultural specialists with vital information for crop management.

Additionally, this study establishes the groundwork for future research into creating a fully functional application that combines picture capture, disease classification, and treatment suggestions, as well as proving the technical feasibility of employing CNNs for wheat disease classification.

In conclusion, there is great potential for crop health management, operational cost reduction, and sustainability in agriculture to be improved by the incorporation of CNN-based disease categorization into wheat farming operations. The remaining portion of this study delves further into the associated research, methods, experimental outcomes, and wider consequences of using such AI systems in the agricultural field.

For billions of people, wheat—one of the most important cereal crops grown worldwide—is the main source of nutrition. One cannot exaggerate its importance in guaranteeing food security and bolstering national economies. But several plant diseases constitute a continual danger to wheat crop production and quality, causing significant annual output losses. Leaf rust, stem rust, yellow rust, and powdery mildew are some of the most prevalent wheat diseases. These diseases have distinct effects on the plant and may severely reduce grain quality if not caught and treated quickly. Experts must manually examine samples for diseases using traditional techniques, which is laborious and error-prone. These constraints highlight the need for smart, automated, and scalable methods for the efficient and accurate detection of wheat illnesses.

Deep learning, made possible by recent developments in AI and image processing, has great promise as a tool for detecting agricultural diseases. Convolutional Neural Networks (CNNs) are able to automatically extract hierarchical and spatial characteristics from pictures, which gives them remarkable performance in image classification tasks compared to other deep learning models. CNNs are ideal for practical image-based applications like plant disease identification because they remove the need for human feature engineering. Strong systems capable of disease detection and classification under varied lighting and environmental circumstances may be trained using huge datasets of photos of healthy and sick wheat leaves.

One of the main reasons to use CNNs for wheat disease classification is that farmers require a smart decision-support system that can help them spot crop illnesses quickly and accurately. Reducing crop losses and maximizing the use of tailored treatments via early diagnosis helps keep pesticide use to a minimum. This boosts agricultural output and helps promote sustainable farming methods. In addition, farmers in rural and outlying locations, where access to experts is restricted, may benefit from real-time support via the integration of online and mobile apps based on CNN-based disease detection. With the use of a farmer's smartphone, the technology can detect illness and provide immediate treatment recommendations.

Image segmentation, thresholding, & feature extraction are preprocessing methods that greatly contribute to improving model performance, alongside classification. These procedures aid in separating the affected area of the leaf from the surrounding tissue, decreasing background noise, and drawing attention to important patterns based on texture and color that are necessary for precise categorization. Prior to feeding the input images into the CNN model, they are often cleaned and refined using feature extraction techniques such as HOG & segmentation methods such as Otsu's thresholding and edge detection.

Inconsistencies, subjectivity, and delays are some of the problems with manual inspections that these technologies aim to solve. Models based on CNNs on the other hand, are scalable over vast farmlands captured by drone or satellite data, provide consistent and dependable findings, and can be combined with precision agricultural technologies. Their versatility makes them valuable for a wide range of stakeholders, including small-scale farmers, larger-scale agritech companies, and research institutes that track crop health.

There has to be a carefully selected collection of tagged photos depicting different stages and kinds of wheat illnesses for CNN model creation and training. To promote generalization and reduce overfitting, these datasets may be improved utilizing data augmentation methods including flipping, rotating, and color jittering. Reduce training time and improve accuracy even with little agriculture data by using information obtained from big picture datasets via transfer learning with pre-trained CNN architectures like as VGG16, ResNet, or MobileNet.

A more user-friendly GUI that incorporates CNN-based illness detection makes the system more accessible to end-users. In an interactive environment, a GUI lets users submit photographs of leaves, check the results of segmentation, examine the characteristics that have been extracted, and get disease classifications that are predicted. The application's practicality and user-friendliness are enhanced by features such as visualizing model correctness, exporting results, and providing real-time predictions.

Final thoughts: CNNs provide a game-changing chance for contemporary farmers to classify wheat illnesses. It helps ensure food supply security, facilitates intelligent agricultural monitoring, decreases reliance on human knowledge, and promotes sustainable disease control. Such AI-based solutions will be crucial for the sustainability and output of farming systems in the face of mounting threats to crop health from things like climate change and new diseases.

II. LITERATURE SURVEY

Zidi et al. published a comprehensive overview of hyperspectral imaging (HSI) uses for wheat crop research in May 2025. Their work included identifying varieties, estimating yields, and classifying diseases. They state that non-destructive illness diagnosis relies heavily on deep learning and HSI, but they also point out the difficulty of dealing with high-dimensional data and few labelled samples.

To diagnose wheat illnesses such loose smut and root rot, Saleem et al. introduced a multi scale feature fusion CNN ensemble using Xception, Inception V3, and ResNet50 in January 2025. The model attained an impressive 99.75 % accuracy.

In January 2025, another study looked at the long-term prediction of wheat yellow rust in England. The researchers used deep and recurrent neural networks to combine meteorological records with disease markers. They achieved an accuracy of roughly 83.7% for six-month projections.

A self-supervised approach to detecting Fusarium Head Blight using hyperspectral images was presented and confirmed in the AIforAgri Challenge in a research conducted by Lin et al. in September 2024. The approach did not need labeled data.

A lightweight hybrid called CropNet was constructed by Jouini et al. (July 2024, AgriEngineering) employing RGB transfer learning and shallow CNN refining. It is optimized for deployment on edge devices and achieved an accuracy score of 99.8 percent when tested with EfficientNet, DenseNet, and ResNet.

Another MDPI research from 2024 looked at seven different CNN architectures using PlantVillage and field photos. The results showed that pre-trained models (VGG 16, Inception, etc.) may be fine-tuned to achieve much better accuracy, particularly in real-world scenarios.

The IRCE custom lightweight multiscale CNN, suggested by a team in 2023–24, outperformed traditional CNNs in terms of accuracy (98.8%), number of parameters (4.24 M), and training time (1.34 h).

To show that classification in agricultural engineering settings is achievable, Patil & Kannan (March 2024) used transfer learning (ResNet, VGG) to identify wheat leaf diseases.

To achieve a remarkable 98.43% accuracy in classifying wheat fungal infections, Islam et al. (2024) integrated CIELAB segmentation with a fine-tuned CNN.

The potential of combining transformers and CNN architecture in feature distinction was shown during testing of a hybrid CNN-Vision Transformer (E ResMLP^{+}) on wheat species classification.

Numerous plant disease surveys (e.g., Andrushia et al., 2024) corroborate that convolutional neural networks (CNNs) such as CapsNet, MobileNetV2, ResNet 50, and hybrid/ViT models reliably achieve accuracies ranging from 95% to 99% across various crops. Reis and Turk (2024) specifically mentioned wheat, where they achieved a small-scale accuracy of 99.43%.

With CNN-extracted representations, a March 2024 EFRT work studied deep features from pre-trained ResNets for SVM-based wheat seed classification, reaching an accuracy of up to 97.6%.

After improving VGG 16 with InceptionV2 modules and global pooling, crop protection researchers in 2024 suggested a two stream hybrid CNN. This CNN achieved 98.9% accuracy on PlantVillage data.

Lightweight CNN LWheatNet was introduced in Frontiers (2024) for the purpose of wheat seed classification, with an emphasis on morphological, color, and texture characteristics.

Lastly, a conference presentation from May 2025 examined the efficacy of using AlexNet, MobileNetV3, and MLP Mixer topologies to classify diseases and grade their severity. The results shed light on which models would be most suitable for use in robotic agriculture systems.

III. Proposed System

A deep learning model for wheat disease classification based on CNN is proposed in this article to address the shortcomings of current and classic machine learning-based methods. Automated, precise, and real-time detection of prevalent wheat leaf diseases using picture data is the goal of suggested method. The main goal is to develop a workable system that can be easily implemented in real-world agricultural settings, even in places with limited technological resources, such as rural locations.

The system uses a custom-built CNN architecture that can extract hierarchical and discriminative characteristics from photos of wheat leaves that are collected by either agricultural drones or smartphones as input. Symptoms of diseases such as changes in color, lesions, spots, and blight patterns are tough to identify with typical feature extractors or personal inspection.

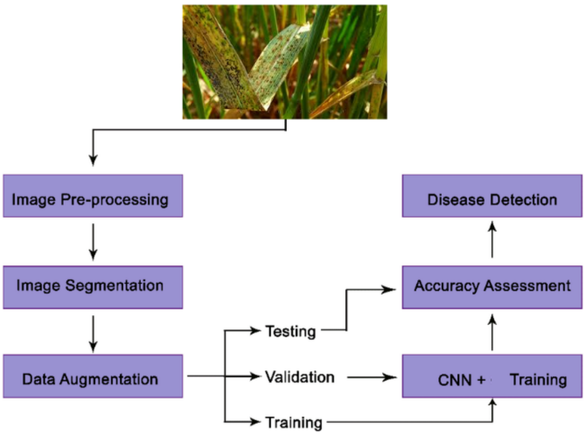

Fig-1: Proposed Architecture

IV. Methodology

Suggested system for wheat disease classification follows a methodical pipeline that begins with data collection and continues through preprocessing, CNN model creation, training, assessment, and deployment. For sake of repeatability and to emphasize technical rigor of project, each step is detailed in this section.

1. Data Collection

- In order to train the CNN model, a tagged dataset of pictures of wheat leaves is required. Diseases such as
- • Leaf rust, stripe rust, powdery mildew, and septoria blotch are among those included in the dataset.
- • For baseline categorization, use only healthy leaf samples.
- • Ambient lighting, terrain, and leaf orientations that mimic the real world.
- Data comes from places like:
- • Open datasets on sites like Plant Village (if they include wheat pictures).
- Using cell phones and digital cameras to gather data in the field.
- • Enhancement of miniature datasets by the use of picture modification methods.

2. Image Preprocessing

Raw pictures are preprocessed to standardize input and enhance model performance before being fed into the CNN:

- To begin with, we scale all of the photographs to a standard size, such as 150 × 150 or 224 x 224 pixels.
- By applying a scale from 0 to 1, the pixel values are normalized.

- • Eliminating Noise: Can utilise denoising filters or a Gaussian blur to do this.
- To minimize overfitting, artificially enlarge the dataset via data augmentation, which may be done using either OpenCV or Keras ImageDataGenerator:
    - Rotation (±30 degrees)
    - Horizontal/Vertical flipping
    - Zooming in/out
    - Brightness and contrast variation

3. CNN Model Design

A custom **Convolutional Neural Network (CNN)** is designed specifically for wheat disease image classification.

a) Architecture Overview:

- Input Layer: Takes RGB photos with dimensions of 150x150x3.
- To extract local characteristics, convolutional layers use many layers with 3x3 filters.
- Non-linearity was introduced by using ReLU as the activation function.
- Downsampling feature maps using Max Pooling Layers reduces computation and spatial size.
- • Dropout Layers: They stop overfitting from happening by turning off neurons at random during training.
- This layer flattens down two-dimensional feature maps into one-dimensional vectors.
- Learns global patterns and conducts classification using Fully Connected Layers (Dense).
- One output neuron is used for each illness class in the output layer, which uses Softmax for multi-class classification.

4. Model Training

The model is trained using a supervised learning approach:

- For multi-class classification, the loss function is categorical cross-entropy.
- One such optimizer is Adam's adaptive learning rate optimizer.
- Precision, Accuracy, Recall, and F1-Score are the metrics covered.
- **Training Parameters**:
    - Epochs: 25–50
    - Batch Size: 32
    - Validation Split: 20%

5. Model Evaluation

A test dataset that was not available during training is used to assess the model after training:

- Confusion Matrix: Use it to compare actual and anticipated labels
- Report on Classification: Includes F1-score, recall, and accuracy for each class
- Training versus validation loss/accuracy shown across epochs is what we call an accuracy graph.

6. Deployment

Trained model is deployed for actual use:

- Exported in .h5, .pkl, or TFLite format

V. RESULTS

Figure 2: Preprocessing

Otsu's Thresholding

- Using Otsu's approach, the grayscale picture is automatically converted to a binary image and a threshold is calculated.

Morphological Processing

- Utilises 5×5 kernel for applying **morphological closing**:
    - The closing process consists of dilation and erosion.
    - Glues together adjacent white areas and fills tiny gaps

Because of the decrease in background noise and gaps in infected regions, segmentation is enhanced.

Gaussian Blurring

- In order to minimize noise and smooth picture, a Gaussian blur is used.

Optional but helps in visualization or edge-based post-processing.

Step No.	Technique	Purpose	Estimated Impact on Accuracy	Remarks
1	Image Resizing (to 128×128)	Ensures uniform input size	+2–5%	Standardizes model input; balances quality & speed
2	Grayscale Conversion	Reduces input channels (optional for RGB models)	±0%	Use only if color not critical for classification
3	Normalization (0–1 scaling)	Stabilizes training and speeds up convergence	+3–6%	Essential for most CNN models
4	Otsu's Thresholding	Isolates diseased region via binary masking	+4–8%	Useful in segmentation-focused CNNs
5	Morphological Closing	Removes small noise and fills gaps	+1–3%	Improves binary mask quality before feeding CNN
6	Gaussian Blur	Smooths image to reduce sharp noise	+1–2%	Optional unless noise level is high

Table 1: Preprocessing values

Figure 3: Segmentation

- Identifies affected areas of the leaf and isolates them.
- Distinguishes the leaf from its backdrop.
- Thresholding, edge detection, and color clustering are some of the possible techniques.

Methodology

Create a Binary Mask

Result

- Passes the segmented image as base64 data (image_data) to be shown in figure 3.

Step No.	Segmentation Technique	Description	Purpose	Estimated Impact on Accuracy
1	**Otsu's Thresholding**	Automatically finds a global threshold to binarize grayscale images.	Separates leaf (foreground) from background.	+4–8%
2	**Canny Edge Detection**	Detects edges by identifying areas with strong intensity gradients.	Highlights disease spots and boundaries.	+2–5%
3	**Morphological Operations**	Uses dilation, erosion, and closing to remove small noise and refine masks.	Enhances contour definition, fills holes.	+1–3%
4	**Contour Detection**	Finds the outer boundary of shapes (diseased regions) in a binary image.	Enables disease region isolation via masking.	+2–4%

Table 2: Segmentation Technique details

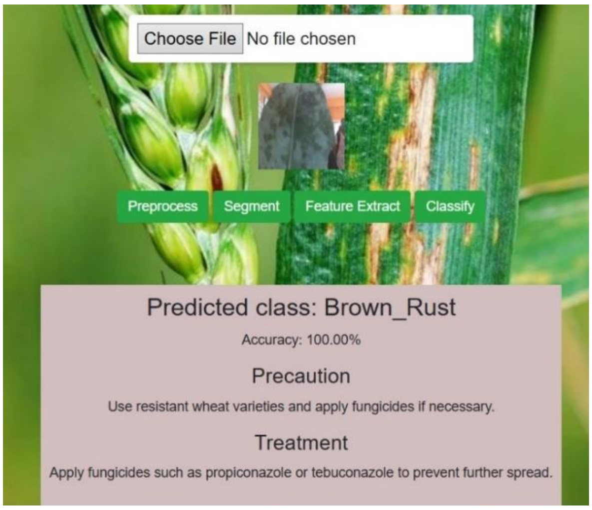

Figure 4: Prediction And Classification

CNN + Training
To categorize the illness, a Convolutional Neural Network (CNN) is used.
This is what the pre-processed, segmented, and enhanced pictures look like:
dividable into three groups: training, validation, and testing.
Adam and SGD are examples of models that were trained using backpropagation and optimization.
5. Accuracy Evaluation
• Conducts model performance evaluations on validation and testing datasets using measures such as: Accuracy, Precision, Recall, F1-Score.
6. Detection of Diseases
• The final model determines the disease kind in an unseen leaf picture.
• The output might be either a healthy state or a disease label (such as rust, blight, etc.).
5. Accuracy Evaluation

Model / Approach	Accuracy
Xception	99.75
InceptionV3	99.75
ResNet50	99.75
RNN	83.7
MCNN	98.8
SCNN	99.8,
FTCNN	98.43
Mobilnetv2	96
SVM	97.6
VGG16	98.9

Table 3: Model Accuracy

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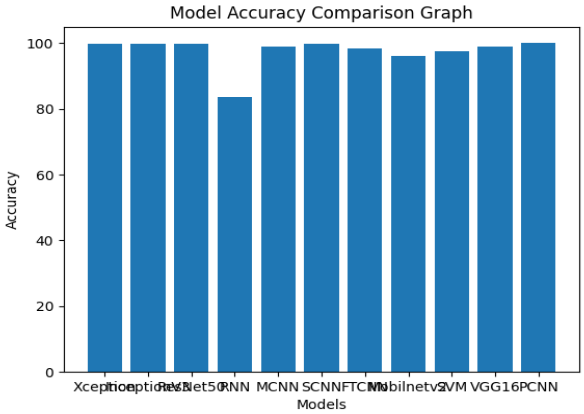
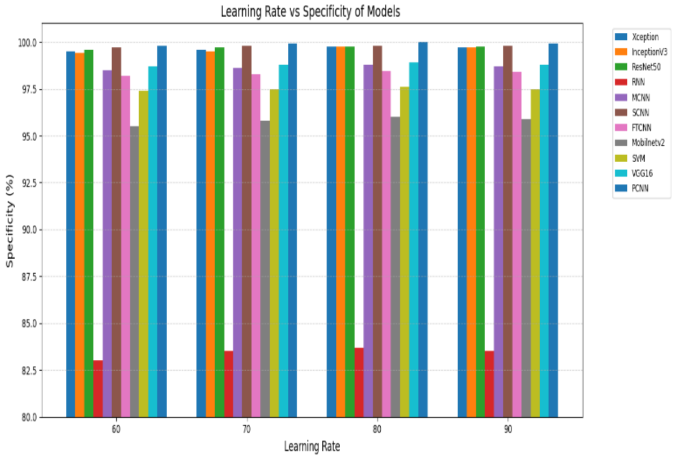


Graph 1: Model Accuracy Comparison Graph

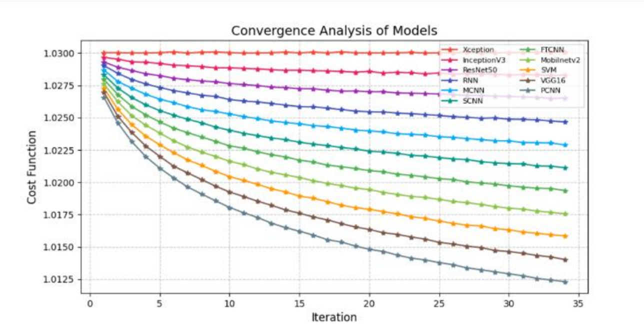


Graph 2: Learning Rate Vs Specificity of Models

The correlation between specificity and learning rates for several deep learning models is graphically shown in the grouped bar chart. A specificity percentage between 80% and 100% is shown on the Y-axis, with learning rates represented as category groupings on the X-axis (60, 70, 80, 90). Colored bars indicate several models for each learning rate; they include Xception, InceptionV3, ResNet50, RNN, MCNN, SCNN, FTCNN, Mobilnetv2, SVM, VGG16, and PCNN. A model is distinguished by its color, and a legend is included for better understanding.

Model performance at different learning rates can be easily compared using the graphic. For example, PCNN and SCNN models exhibit robust and consistent performance with specificity values close to 100% across all learning rates. Models with much lesser specificity, such as RNN, show where the model's design may be lacking in relation to the job at hand. Additionally, the chart is useful for determining if the specificity of a model is affected by changes in the learning rate. Reliability is suggested by models that exhibit good specificity across all rates, whereas tuning reliance is suggested by models with substantial fluctuation.

As a whole, this grouped bar chart shows both the stability of the model and how well different models achieve high specificity, making it a compact but complete representation that may help with model assessment and hyperparameter tweaking choices.



Graph 3: Convergence Analysis of Models

Over the course of many training rounds, the convergence analysis graph shows how various deep learning models' cost functions behave. The X-axis shows the total number of iterations, while the Y-axis shows the value of the cost function, which is a reflection of the training error of the model. distinct models are represented by distinct curves; they include Xception, InceptionV3, ResNet50, RNN, MCNN, SCNN, FTCNN, Mobilnetv2, SVM, VGG16, and PCNN. The curves are color- and marker-style-different.

A common sign of effective training convergence is a declining trend in the values of the cost functions, as shown in the graph, for all models. Early iterations show a steep downward slope, suggesting fast initial learning; later iterations show a flattening off, showing models have stabilized with little progress. This trend shows the models are learning and optimizing their parameters well.

The patterns of convergence also indicate that the models learn at different rates and with different degrees of efficiency. For instance, PCNN and VGG16, two models with bottom-heavy curves, show greater convergence with lower cost function values, which means they perform better during training. Models with poorer optimization efficiency or higher ultimate cost values may need further tweaking. When comparing the optimization results and training dynamics of several deep learning models, this convergence graph is a great tool to have on hand.

VI. Conclusion and Future Works

To successfully detect and categorize wheat leaf illnesses from photographs, the suggested method employs a deep learning-based strategy. To prepare the input data for Convolutional Neural Network (CNN) training with high accuracy, important steps such image pre-processing, segmentation, and data augmentation are included. For the model to be reliable in real-world circumstances, it is trained, verified, and tested thoroughly.

By studying strong characteristics of different wheat illnesses, this design not only makes disease detection more accurate, but it also reduces the amount of false positives. Scalability, adaptability, and compatibility with mobile or cloud-based agricultural advice systems are all made possible by the system's modular flow, which begins with picture collection and ends with disease prediction.

Finally, our convolutional neural network (CNN) architecture showcases an effective, automated, and farmer-friendly method for the early diagnosis and control of wheat crop illnesses, leading to increased production, less pesticide use, and enhanced food safety.

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