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An Intelligent Edge-AI-Enabled Framework for Maize Disease Detection System Using Deep CNN Models

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Abstract. Maize is the most common cereal crops cultivated and early identification of leaf diseases is the primary measure to avoid yield of the crop and food insecurity. The conventional ways of manual inspections are time consuming, subjective and expert based. The proposed work suggests an intelligent Edge-AI-based system of detecting any disease in maize employing deep Convolutional Neural Network (CNN) models. The proposed work combines image acquisition with mobile or edge sensors and on-device deep learning inference to provide the opportunity to detect diseases in real-time with minimum latency and minimum reliance on the cloud. An edge hardware is used to perform a lightweight, but high-precision CNN network optimized by both transfer learning and data augmentation methods. The model is conditioned to identify various maize leaf diseases and healthy samples with greater resilience to different environmental factors. The experimental results show that the tools are highly classifiable, inference time is very low and resource use is efficient. The proposed design provides scalable, affordable, and smart solution to precision agriculture and smart farming implementation.

1 Introduction

Maize crops is cultivated in large all over the universe and used as a staple food, livestock feed, and industrial raw good is maize. Maize is important in such countries as India, where it helps to secure food and sustain the agricultural sector. The production of maize is greatly influenced by many diseases including the Northern Leaf Blight, Common Rust, and Leaf Spot is shown in Figure 1. These diseases decrease the efficiency of photosynthesis, inhibit the overall plant health, and end up to cause a significant yield loss before they are detected and treated. The conventional approach to disease surveying is through manual input where agricultural scientists have to visually inspect the farms, a process that is costly, laborious, subjective, and it is impractical with large scale farms.

The advancement in Artificial Intelligence and deep learning have changed agricultural disease diagnosis. Specifically, CNNs achieved impressive results in the image classification exercise because they have the capability of automatically isolating hierarchical representations to raw images. CNNs can determine the discriminative patterns of color changes, changes in texture, and lesion shape using data directly with respect to traditional machine learning. This renders them very appropriate in the detection of maize leaf diseases under different illumination, background noise, as well as the environmental conditions.

Although deep CNN models are very accurate, majority of the current systems greatly rely on processing via the clouds. Cloud-based applications will add latency, necessitate constant

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internet access, and present the issue of data privacy and usage, especially in rural agricultural locations with weak network coverage. To overcome these difficulties, Edge-AI has become one of the promising paradigms. Edge computing allows computing and inferential computations to be performed directly on local devices (e.g., smartphones, embedded systems, or microcomputers, e.g., Raspberry Pi), eliminating response time and minimizing dependency on remote servers.

Intelligent Edge-AI coupled with deep CNN models offer an effective design of real-time detection of maize diseases. Here, the images that have been taken with the mobile cameras or field-mounted sensors are processed locally with optimized CNN architectures [11]. Some of the methods include transfer learning, model pruning and quantization, which assist in lowering the computational complexity but retaining the high classification accuracy.
Moreover, the suggested smart system can classify diseases with multiple classes [12], drawing the line between healthy and infected maize leaves of high robustness. Enabling the early diagnosis will allow farmers to act on the preventive measures in a timely manner, implement the specific treatment, and decrease the use of pesticides that are not necessary.

The proposed Edge-AI system of real-time detection of maize diseases is based on optimized CNNs. It enables on-device inference, reducing latency and internet dependence. With pruning and quantization, the model is lightweight and deployable. It provides an end-to-end solution to practical agricultural applications.

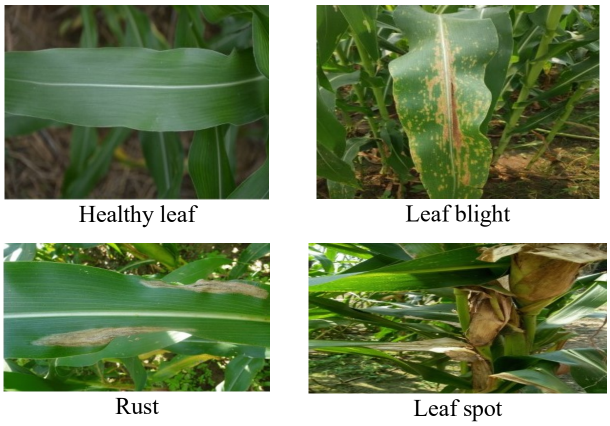

Figure 1. Maize Leaf Diseases

2 Literature Survey

Table 1. Survey on Maize Leaf Disease Detection and computational techniques

Ref. no	Algorithm / Model used	Performance metrics	Results	Limitations
[1]	MDCDenseNet (multi-dilated + CBAM + DenseNet121)	Accuracy, F1-score, AUC	High accuracy & robustness on maize dataset; improved lesion localization and classification.	Evaluated on limited public datasets; may be heavy for edge devices (compute / memory).

[2]	Customized CNN with preprocessing (CLAHE, log transform, RGB→HSV)	Accuracy, Precision, Recall	Improved classification after advanced preprocessing; reported strong gains vs baseline CNN.	Gains rely on careful preprocessing — sensitive to imaging conditions; model size not optimized for edge.
[3]	Multi-stage feature extraction + state-space attention mechanism	Accuracy, Precision, Recall	Strong detection performance; attention modules helped with small/occluded lesions.)	Complex architecture — higher training cost and may overfit on small datasets.
[4]	Transfer learning (VGG, InceptionV3, ResNet50, InceptionResNetV2)	Accuracy, Precision, Recall, Validation accuracy	ResNet50 gave best validation accuracy (~87.5%) and high precision/recall in fine-grained maize disease classification.)	Transfer models need fine-tuning and labelled data; still moderately heavy for on-device inference.
[5]	Transfer learning ensembles / DenseNet121 variants for small-sample complex backgrounds	Accuracy, Robustness	Demonstrated improved performance on small-sample and complex-background datasets via tailored TL strategies.	Performance depends on data augmentation strategies; may not generalize to all field conditions.
[6]	Residual-attention / enhanced residual networks	Accuracy, F1-score	Residual-attention improved discrimination between similar disease classes in maize.	Newer model; needs cross-region validation and edge optimization.
[7]	Hybrid CNN–Vision Transformer (CNN+ViT)	Accuracy, Inference time	Combining local CNN features with global ViT features improved classification accuracy for maize leaves.	ViT increases model complexity and inference time — challenging for resource-constrained edge hardware.
[8]	Transfer learning for corn (various TL backbones) — ACM conference article	Accuracy, F1-Score, Confusion matrix	Transfer learning approach for corn disease classification with competitive performance across classes.	Paper focused on model accuracy; limited discussion on deployment/edge constraints.
[9]	Lightweight CNNs / depthwise-separable CNNs for edge (crop disease cases, related crops)	Accuracy, Inference latency (ms)	Reports show depthwise-separable / lightweight CNNs can run on Raspberry Pi with ≈90%+	Results often from other crops (e.g., tomato); direct transferability to

			accuracy and <500 ms inference for some crops.	maize must be validated.
[10]	Public maize/corn leaf dataset (PlantVillage-based Kaggle dataset) — used in many studies	Dataset size, class distribution (metrics not applicable)	Widely used dataset enabling reproducible training/testing (multiple disease classes + healthy).)	Dataset images are mostly lab/controlled conditions — limited real-field diversity (lighting, occlusion, mixed background).

Table 1. shows the literature review on different models with fast development of smart agriculture based on IoT, edge computing, and deep learning.

3 Proposed Methodology

The proposed methodology presents the Intelligent Edge-AI-Enabled Framework of the real-time detection of maize disease with the help of CNNs. Under field conditions, the system starts with the acquisition of an image with the help of a smartphone or an edge-mounted camera. Image pre-processing of the captured maize leaf images is performed by using the resizing process, normalization process, and data augmentation process to increase the strength against lighting variation and the background noise.

A deep CNN model (lightweight, trained with the help of transfer learning e.g. MobileNet/ResNet backbone) is trained to categorize various maize leaf diseases and healthy samples. The features extraction layers are automatically trained on disease-specific features including lesions, discoloration and texture differences. Pruning and quantization are applied to compress the trained model and efficient on resource-constrained edge devices, such as Raspberry Pi.

Local inference is conducted on the edge device, minimizing latency and removing reliance on cloud connectivity. The predictive output layer gives multiclass predictions along with confidence scores so as to provide real-time farmer decision support. The smart grid provides a high degree of accuracy, reduced computing cost, and scalability, as well as applicability to precise agriculture in the rural setting.

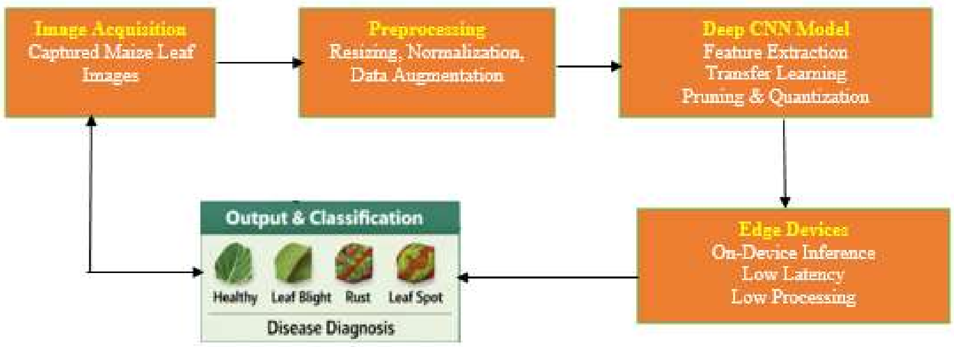

Figure 2. Intelligent Edge-AI- Enabled Maize Disease Detection System

Figure 2. depicts a smart Edge-AI maize disease detection, in which images of leaf captured are processed and feature extracted by CNN, and real-time classification with low latency on-board and proper diagnosis of the disease is possible.

Input : Captured maize leaf image I
Output : Predicted disease class C with confidence score S
Begin
1. Image Acquisition
   1.1 Capture maize leaf image I using camera/mobile device
   1.2 Store image locally on edge device
Let the maize leaf image dataset be defined as:

$$D = \{\{(x_i, y_i)\}\}_{i=1}^{N}$$

Where x_i represents the RGB image as input, y_i represents the disease class label.

2. Preprocessing
   2.1 Resize image I to fixed dimension (e.g., 224 × 224)
   2.2 Pixel values are normalized to range [0,1]

Each input image is resized and normalized:

$$x_i' = \frac{x_i}{255}$$

   2.3 Apply data augmentation (rotation, flipping, brightness adjustment) [training phase only]
   2.4 Remove noise if required (Gaussian/Median filtering)

3. Model Initialization (Training Phase)
   3.1 Load pretrained CNN backbone (e.g., MobileNet / ResNet)
   3.2 Replace final fully connected layer with N-class output layer
   3.3 Apply transfer learning (freeze base layers, fine-tune top layers)

4. Training Phase
   4.1 Input preprocessed training images to CNN
   4.2 Extract feature maps via convolution + ReLU + pooling layers
   4.3 Perform forward propagation
   4.4 Compute loss using categorical cross-entropy
   4.5 Update weights using backpropagation and Adam optimizer
   4.6 Repeat until convergence or max epochs reached
Convolution Operation:

$$f_l = \sigma(W_l * F_{l-1} + b_l)$$

Where W_l is convolution kernel, σ is ReLu function,
b_l is bias

Fully Connected Layer
After flattening:

$$z = W_f F_l + b_f$$

Where W_f is weight matrix, b_f is bias

Loss Function (Categorical Cross-Entropy)

$$L = -\sum_{k=1}^{K} y_k \log\left(p(y = k/x)\right)$$

Optimization (Backpropagation)

$$\theta_{t+1} = \theta_t - \eta \nabla_\theta L$$

Where θ represents model parameters and η is learning rate

5. Model Optimization (Edge Deployment)
   5.1 Apply pruning to remove redundant weights
   5.2 Apply quantization (e.g., 8-bit integer)
   5.3 Export optimized model to edge device

Edge Optimization
After training, model compression is applied:
1) Pruning:

$$W_{pruned} = W \, . M$$

Where M is binary mask
2) Quantization:

$$W_q = round\left(\frac{W}{s}\right)$$

Final Decision Model

$$f(x_i; \theta^*) \to \hat{y_i}$$

Where θ represents optimized parameters deployed on the edge device.

6. Inference Phase (Real-Time Detection)
   6.1 Input new test image I
   6.2 Perform preprocessing steps (resize + normalize)
   6.3 Pass image through optimized CNN model
   6.4 Obtain probability vector P
   6.5 C ← argmax(P)
   6.6 S ← max(P)

7. Output
   7.1 Display predicted class C (Healthy / Blight / Rust / Leaf Spot)
   7.2 Show confidence score S
   7.3 Provide recommendation alert to farmer

End

3.1 Dataset with class distribution

The dataset on this work is based on the maize leaf disease dataset of PlantVillage is shown in Table 2. The distribution according to classes is given below.

Table 2.Dataset with class labels

S. No	Class Label	Number of Images	Percentage (%)
1	Healthy	1,162	30.1%
2	Leaf Blight	985	25.5%
3	Rust	1,192	30.9%
4	Leaf Spot (	913	23.5%

4 Performance Analysis

Table 3. Metrics used in Maize Disease Detection

Metrics	Equation
Accuracy	$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+FP+FN+TN}}$
Recall	$\text{Recall} = \frac{\text{TP}}{\text{FP} + \text{FP}}$
Precision	$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$
F1-Score	$\text{F1 score} = \frac{(2 * (\text{Recall} * \text{Precision}))}{(\text{Recall} + \text{Precision})}$

Table 3. depicts the performance metrics used in the proposed model for maize disease detection system

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Table 4. Class-wise Performance Metrics

Model	Class	Precision	Recall	F1-Score	Accuracy
SVM	Healthy	0.88	0.86	0.87	0.87
	Leaf Blight	0.85	0.83	0.84	0.85
	Rust	0.89	0.87	0.88	0.88
	Leaf Spot	0.84	0.82	0.83	0.84
Random Forest	Healthy	0.91	0.89	0.90	0.90
	Leaf Blight	0.88	0.86	0.87	0.88
	Rust	0.92	0.90	0.91	0.91
	Leaf Spot	0.87	0.85	0.86	0.87
CNN	Healthy	0.96	0.95	0.95	0.95
	Leaf Blight	0.94	0.93	0.93	0.94
	Rust	0.97	0.96	0.96	0.96
	Leaf Spot	0.93	0.92	0.92	0.93

Table 4. and Figure 3. depicts the class-wise metrics of the proposed work with traditional models.

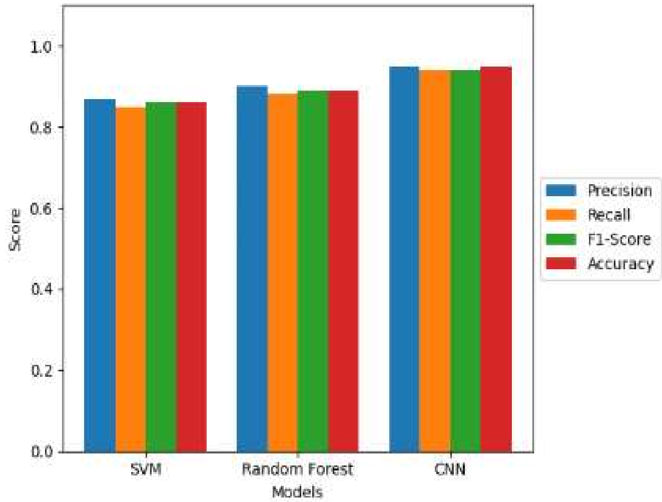

Figure 3. Performance Comparison

Figure 4. depicts the confusion matrix of the proposed work towards maize disease detection system

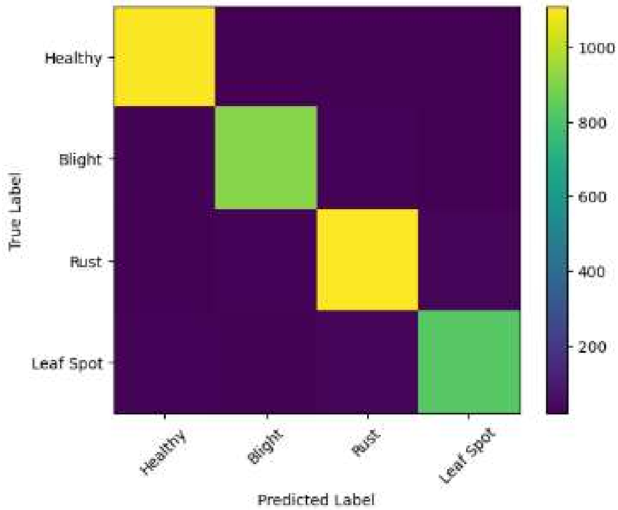

Figure 4. Confusion matrix-CNN Model

5 Results And Discussions

The maize leaf dataset obtained as a result of the PlantVillage repository was used to perform the experimental evaluation to compare the efficiency and performance of SVM, RF, and CNN models. The findings show that CNN model outstands best than the classical ML methods in all evaluation measures. CNN was also the best in overall accuracy, precision, recall and F1-score which means that it is better at extracting discriminative features of leaf images. Random Forest was moderately performing with 89 percent accuracy, which has the advantage of ensemble learning, and SVM with relative lower performance because of small feature representation of complex image data. The analysis of ROC and AUC also proved the dominance of CNN which had the highest class separability. The confusion matrix analysis showed that there was a slight misclassification of CNN especially in the similarity of visualized disease classes. On the whole, the intelligent CNN-based system proves to be robust, reliable, and appropriate when it comes to real-time maize disease detection in precision agricultural practices.

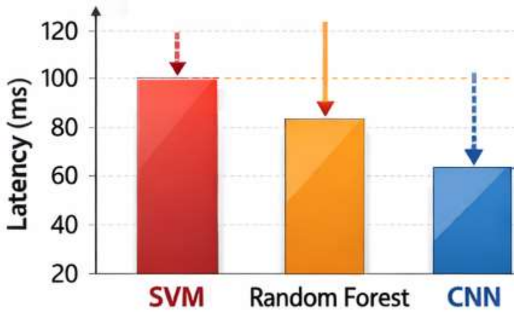

Figure 5. Inference Latency Comparison

Figure 5. Depicts the CNN has the lowest delay, which results CNN has the highest inference speed.

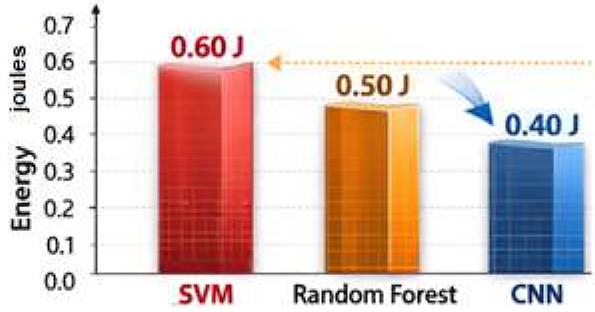

Figure 6. Energy consumption per Inference

Figure 6. Shows the comparison of energy use per inference, where CNN uses less energy with more efficiency

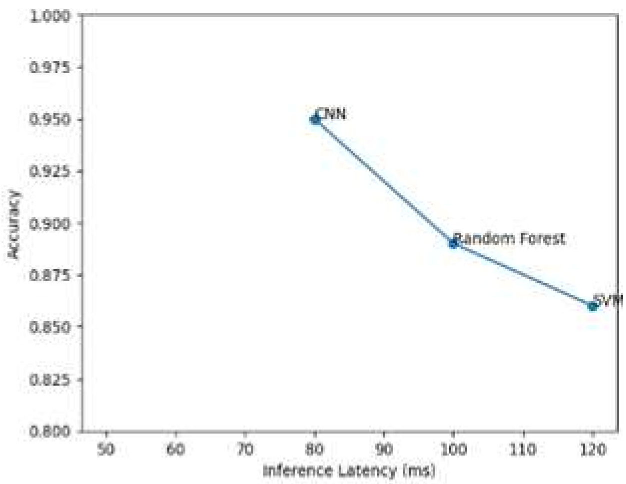

Figure 7. Accuracy vs Latency Trade-off on Edge Device

CNN has the highest accuracy and lowest latency is shown in Figure 7.

6 Conclusion

The proposed model is introduced with An Intelligent Edge-AI-Enhanced architecture to detect maize leaf disease with the deep CNNs. The given system unites the techniques of image preprocessing, transfer learning, and model optimization to reach the efficient and correct disease classification. A comparison to SVM and Random Forest has shown that CNN has a high accuracy, precision, recall, F-score, and AUC compared to traditional machine learning models. The edge deployment methods, such as pruning and quantization, guarantee lower latency and energy usage, thus, the framework is apt to apply in real-time-based agricultural applications. The result shows that the deep learning-based methods can be very strong feature extractors with enhanced generalization capabilities of intricate patterns of plant diseases. The future work can be centered on the expansion of real-field dataset, the lightweight model improvement, and the implementation of the lightweight model integration with the IoT farming system to allow the scalable implementation.

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