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A LIGHTWEIGHT CUSTOMIZED CNN MODEL FOR EFFICIENT AND REAL-TIME POTATO LEAF DISEASE DETECTION

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Abstract: Potato is a staple crop around the world, but its yield is seriously threatened by fungal diseases like Late Blight and Early Blight. Deep learning has shown a lot of potential in automated disease detection. However, many existing models like VGG16 and ResNet50, are complex and have large parameter. This restricts their use on devices with limited resources. This paper introduces a Lightweight Custom Convolutional Neural Network (LCCNN) that aims to balance high classification accuracy and improved efficiency. The model was trained and validated with the Plant Village dataset. This dataset contains images of Late Blight, Early Blight, and Healthy potato leaves. By using a simple structure with about 1.9 million parameters, the proposed model significantly lowers memory use compared to traditional architecture. As we can say that VGG16 require about 138 million parameters, ResNet50 uses around 25 million parameters, and DenseNet121 which needs 8 million parameters. Experimental results show that LCCNN reaches a testing accuracy of 99.2%. This precision, recall and F1-scores are above 98% in each category. The model's low latency and high accuracy make it suitable for IOT based farming, mobile applications and real time disease detection.

***Keywords*—Potato leaf disease detection, Lightweight Customized Convolutional neural network (LCCNN), Image-based classification, Precision Agriculture, Edge Computing, IoT-based Farming, Real-time Disease Detection.**

1. Introduction

Potato is an important crop around the world. It helps provide food security and supports sustainable farming. However, potato cultivation is highly susceptible to foliar diseases, particularly early blight and late blight, which significantly reduce crop yield and quality if not detected at an early stage [10–12]. These problems create a major challenge for farmers because the diseases spread quickly and can cause heavy losses to farmers, especially where there is limited expert advice. Early blight, caused by Alternaria species, and late blight, caused by Phytophthora infestans. These two are the most damaging diseases for potatoes. Both diseases have similar symptoms in the beginning stages, which makes it difficult to identify them correctly [11,12]. Traditional diagnosis methods rely on visual inspections by experienced agronomists. This process is time-consuming, subjective, and not effective for large farms or remote areas. Delays in diagnosis can result in excessive pesticide use, increased production costs, and permanent harm to crops [10–12]. In recent progress of machine learning (ML) and deep learning (DL) have has allowed for automated plant disease detection using image analysis techniques. Convolutional neural networks (CNNs) excel at extracting key features from plant leaf images, which helps features from plant leaf images, which helps classify healthy and diseased crops [6,8,10]. The existence of large annotated datasets, such as the plant village dataset, has also aided the development and examination of automated disease detection models [13]. Despite these advancements, using automated disease detection systems in real-world farming remain challenging due to practical issues. These challenges are limited computing power and the need for quick decision support. As a result, there is a strong demand for efficient and scalable disease detection solutions. These solutions should function well on mobile devices and edge computing platforms, especially to assist the farmers in resource limited areas.

2. Literature Review

Radwan, M. et al. [1] has studied machine learning models to predict potato diseases using over 4,000 weather records. They examined factors like humidity, wind speed, temperature, and pressure to understand disease spread, using techniques such as PCA, K-means clustering, and copula analysis. They tested different machine learning models such as logistic regression, gradient boosting, multilayer perceptron (MLP), support vector machine (SVM), and K-nearest neighbour (KNN), both with and without feature selection included. Using Binary Grey-lag Goose Optimization, they found that the MLP model performed best with feature selection, achieved the accuracy of about 98.3%. El-Kenawy, E. S. M. et al. [2] introduced the hybrid method called GGGWO that combines the Greylag Goose Optimizer (GGO) and the Grey Wolf Optimizer (GWO). It aims to improve CNN models for classifying potato diseases and helps make detection faster and more accurate. They tested the model and compared it with other optimization algorithms using ANOVA and Wilcoxon signed-rank. The result showed that the GGGWO-CNN model achieved a very high accuracy of 99.04% and a sensitivity of 94.21%. This proves that the method is effective for detecting potato diseases and can help farmers in precision agriculture. Barman et al. [3] developed a hybrid deep learning model using EfficientNetB for feature extraction and SVM for classification. This model detects late blight in potatoes, brown spot in rice, and common rust in corn. It achieved 97.29% accuracy, which is better than CNN, VGG16, ResNet50, Exception, MobileNetV2, Autoencoders, Inception v3, and standalone EfficientNetB0, showing it works well for detecting diseases in multiple crops.

Alhammad, S. M. et al. [4] proposed a model for classifying potato leaf disease using transfer learning with Grad-CAM. The model was trained on a public dataset where it achieved 97% validation accuracy and 98% testing accuracy, showing that by combining Grad-CAM with transfer learning, the model performs extremely well.

Alzakari, S. A. et al. [5] used a CNN-LSTM architecture to detect potato leaf diseases, applying Z-score normalization and evaluating it against algorithms such as Random Forest, Extra Trees, KNN, AdaBoost, and SVM. In this model, CNN layers extract spatial featureswhile LSTM captures sequential patterns. Using various metrics like accuracy, specificity, sensitivity, F-score, and AUC, the CNN-LSTM model reached 97.1% accuracy, indicating it is highly effective for automated potato disease detection. Sarada et al. [6] developed a CNN based model for early detection potato leaf diseases using the PLD dataset, which contains 4,072 images. The model reached 98.2% accuracy, enabling timely diagnosis, reducing crop loss and supporting precision farming. Farooq et al. [7] introduced Zero-Shot CNN by integrating CNNs with Zero-Shot Learning to classify both known and unknown plant diseases using semantic embeddings. And when they tested the model on the Kaggle potato disease dataset, it achieved outstanding, 98.50% accuracy for known classes and 99.91% for unknown classes. This approach works better than traditional CNNs and offers a scalable, real-time solution for the detection crop diseases.

Tadesse et al. [8] created the deep learning model to classify potato leaf diseases and evaluate their severity. They have used 4,200 smartphone images for dataset, after developing the model, it reached extremely high accuracy of a 99% for identifying disease types and 96% for severity levels. The model performed better than Alex-Net and VGG16, making it useful for precision agriculture and crop management. Singh et al. [9] developed and proposed an ensemble CNN model that integrates MobileNetV2, VGG16, and ResNet50. They have trained the model with a combined dataset of 6,644 potato leaf images collected from three countries. The model performed outstanding reaching an accuracy of 98.49%, which is better than any individual networks. It was also deployed on a web platform, showing how effective ensemble learning is for detecting crop diseases. Zhang et al. [10] improved early blight and viral disease detection using a lightweight VGG16S model enhanced with CBAM, global average pooling, and Leaky ReLu. With approximately 15M parameters and dataset augmentation, it achieved 97.87% accuracy, outperforming ResNet50, MobileNetV1, and Vision Transformer, making it suitable for resource limited agricultural settings. A summary of reviewed literature is provided in Table 1.

Although recent studies have achieved high accuracy in potato leaf disease detection using the deep learning and Hybrid models, most approaches rely on computationally expensive architectures such as VGG16, ResNet50, ensemble CNNs, or optimization-heavy frameworks. These models often involve large parameter sizes, high memory consumption, and increased inference latency, which restrict their deployment on resource-constrained devices. Additionally, several works emphasize accuracy improvement without adequately addressing real-time performance and edge suitability. Limited attention has been given to designing fully custom, lightweight CNN architectures optimized specifically for mobile and IoT-based agricultural applications. There is a clear need for an efficient, low-parameter, real-time disease detection model. This model must maintain high accuracy while being practical for use in the field.

Table 1: Summary of Reviewed Literature

Sl. no	Author(s)	Year of Publication	Model / Study Title	Algorithms used	Dataset Used	Accuracy
1	Radwan, M. et al. [1]	2025	Potato Leaf Disease Classification Using Optimized Machine Learning Model	Logistic Regression, Gradient Boosting, MLP, SVM, KNN and bGGO	Weather records and disease data with feature selection	98.3%
2	El-Kenawy, E. S. M. et al. [2]	2025	Optimizing Potato Disease Classification Using a Metaheuristics Algorithm for Deep Learning	GGGWO-optimized CNN	Kaggle Potato Leaf Disease Dataset	99.04%
3	Barman, S. et al. [3]	2024	Optimized Crop Disease Identification in Bangladesh: A DL and SVM Hybrid Model	EfficientNetB0 (feature extractor) and SVM	Multi-crop image dataset (Rice, Potato, Corn)	97.29%
4	Alhammad, S. M. et al. [4]	2025	Deep Learning and Explainable AI for Classification of Potato Leaf Diseases	Transfer Learning-based CNN and Grad-CAM (XAI)	PlantVillage dataset	98.0%
5	Alzakari, S. A. et al. [5]	2025	Early Detection of Potato Disease Using an Enhanced CNN-LSTM Model	CNN-LSTM , RF, ET, KNN, AdaBoost, SVM	Standardized image dataset (Z-score normalization)	97.1%
6	Sarada, J. et al. [6]	2024	Early Stage Disease Classification in Potato Leaves Using CNN	Custom CNN	PLD Dataset (4072 images: Healthy, Early Blight, Late Blight)	98.2%
7	Farooq, M.S. [7]	2025	Advancing Early Blight Detection in Potato Leaves Through ZeroShot Learning	ZeroShot CNN with semantic embeddings	Kaggle Potato Disease Dataset	98.5% (seen), 99.91% (unseen)
8	Tadesse, A. D. et al. [8]	2025	Deep Learning-Based Potato Leaf Disease Classification and Severity Assessment	Custom CNN (compared with AlexNet, VGG16)	Smartphone images (4200 leaves with severity levels)	99% (disease), 96% (severity)
9	Singh, G., Kasana, G., & Singh, K. [9]	2024	Improved Potato Crop Disease Classification Using Ensembled CNN	Ensemble of VGG16, MobileNetV2, ResNet50	Combined datasets (6644 images from multiple regions)	98.49%
10	Zhang, C. et al.[10]	2025	Research on a Potato Leaf Disease Diagnosis System	Improved VGG16S (CBAM, GAP, Leaky ReLU)	Augmented dataset (Early Blight & Viral diseases)	97.87%

Based on existing studies that primarily use heavyweight deep learning models such as VGG16, ResNet50, and DenseNet121 for plant disease detection, can a lightweight custom convolutional neural network be designed to achieve comparable or improved classification accuracy while significantly reducing model complexity and parameter count? Considering the increasing demand for smart agriculture solutions, is it possible to develop and deploy an efficient deep learning model for real-time potato leaf disease detection on resource-constrained platforms such as IoT devices and mobile applications without compromising classification performance?

3. Proposed Methodology:

In this section the RQ1 is discussed. The Proposed methodology establishes a comprehensive framework for the automated detection of potato leaf diseases, with a strategic focus on computation efficiency for edge device development. It consists of four primary phases i.e., data acquisition and curation, image preprocessing and augmentation, LCCNN model design, and rigorous performance evaluation. Figure 1 shows the workflow of the Proposed LCCNN model.

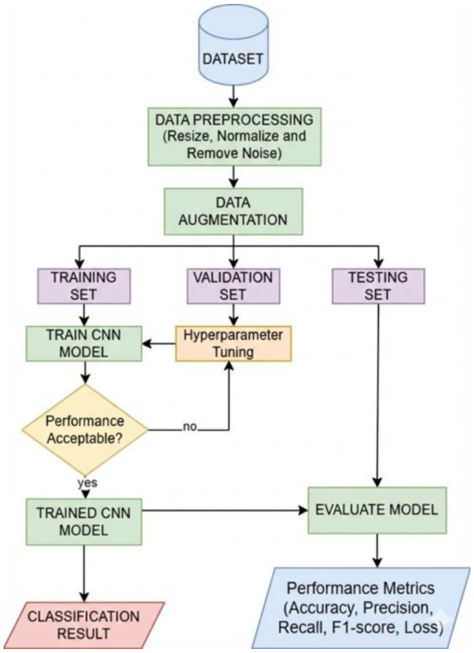

Figure 1: Workflow Diagram of Proposed CNN Model

3.1 Dataset Description and Splitting:

We have utilized PlantVillage Potato Leaf dataset [13], one of the widely used dataset in agriculture deep learning, for our experimental analysis. The dataset consists of a total of 2,152 RGB images divided into three of distinct classes: Early Blight infected leaf, Late Blight infected leaf, and the vibrant green Healthy leaf. We have divided the dataset into 80:10:10 ratio: 80% of the images are for the training 10% images are for the validation, and rest 10% images are for testing. To visually understand how the infected leaf looks like compared to the healthy ones, Figure 2 shows Healthy and infected samples from the PlantVillage dataset.

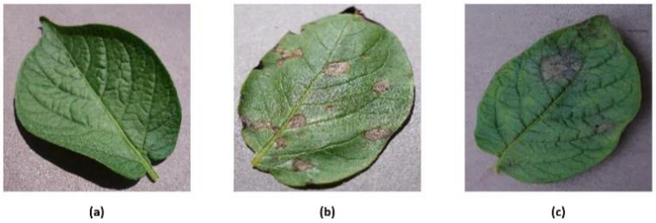

Figure 2: Represents (a) Healthy Leaf, (b) Early Blight infected leaf and (c) Late Blight infected Leaf.

3.2 Preprocessing and Augmentation:

We have used different techniques to improve the model's performance and make it more reliable in real world farming conditions. Initially, the images were standardized to 256 x 256 pixels size and values were normalized to range [0,1]. This helps the model learn more efficiently by smoothing the training process. We have artificially expanded our training set using data augmentation to tackle the common challenge of overfitting. By applying random flips, rotations, and shearing effects.

3.3 Existing Deep Learning Architecture:

VGG16 is a foundational deep learning convolutional neural network which utilizes a sequence of 13 convolutional layers, all featuring fixed 3 × 3 kernel size followed by the max pooling operations. While its depth facilitates the learning of complex hierarchical features, However, its requires a very large parameter count of approximately 138 million making it unsuitable for deployment on resource constrained devices, despite its strong representational capacity. Equation 1 defines the convolutional operation performed at each layer of VGG16:

$$F_{i,j,k} = \sum_{m=1}^{M} \sum_{n=1}^{N} \sum_{c=1}^{C} W_{m,n,c,k} \cdot X_{i+m,j+n,c} + b_k \tag{1}$$

Equation 2 defines the Spatial dimensionality reduction which is achieved using max-pooling:

$$P_{i,j} = \max_{(m,n)\epsilon\Omega} F_{i+m,j+n} \tag{2}$$

ResNet50 is a famous deep Learning Convolutional Neural Network with 50 layers. It addresses the common degradation problem in the deep neural networks by implementing residual learning blocks. The 50 layers' architecture enable the network to learn deeper and more discriminative features. While ResNet50 achieves superior performance compared to traditional CNNs, it still involves computational complexity and high parameter count, limiting its application in real time edge based agricultural systems The residual learning mechanism in ResNet50 is mathematically expressed as:

$$y = \mathcal{F}(x, W) + x \tag{3}$$

This identity mapping enables efficient gradient flow during backpropagation, thereby stabilizing training in deep architectures.

DenseNet121 is a widely used architecture of Densely Connected Convolutional Network, introduced by Gao Huang, Zhuang Liu, Laurens van der Maaten, and Kilian Q. It is a type of deep learning model for computer vision that connects every layer within a block to all preceding layers in a feed forward manner. DenseNet121 architecture is designed to reuse features efficiently, enhances gradient propagation, and minimizes redundancy in learned features. With relatively smaller no. of parameters approximately 8 million, it achieves high classification accuracy. Despite this advantage, the dense connectivity increases memory and computation requirements. This makes real-time deployment on low-power devices more difficult. The dense connectivity pattern is mathematically defined in equation 4:

$$x_l = H_l([x_0, x_1, \ldots, x_{l-1}]) \tag{4}$$

The mathematical formulation supports effective feature reuse while reducing gradient weakening across deeper layers.

3.4 Proposed CNN Architecture

In this section the RQ2 is discussed. The main contribution of this work is the design of a Lightweight Custom CNN (LCCNN) architecture that offers a parameter-efficient alternative to widely used deep models such as VGG16 and ResNet50. In the LCCNN model, the number of filters gradually increased to learn features effectively. It starts with 32 filters to capture basic visual details such as edges and color changes. As shown in Figure 3, the model accepts image of size (256, 256, 3) and processes it through six convolutional blocks. The initial block uses a 3 × 3 kernel and is followed by a Max Pooling layer. Next, it followed by three blocks with 64 filters and later by blocks with 128 filters. This step by step increase in filters helps the network move from detecting simple textures to identifying high level disease characteristics. Following the final feature extraction stage, the spatial information is transformed into a global descriptor via a flattening operation and the one dimensional vector is passed to a dense layer consisting of 128 neurons activated by the Rectified Linear Unit (ReLU) function. The network terminates in a 3 way Softmax layer, which maps the high level features to a probability distribution across the target blight classes. This design results in offering a significant reduction in computational cost compared to others or traditional models with minimum parameters.

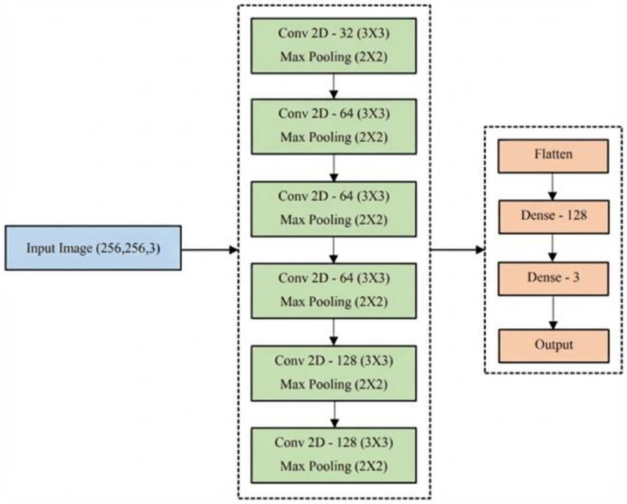

Figure 3. Proposed CNN Architecture

3.5 Training Configuration

The LCCNN was built using TensorFlow/Keras and was Trained for 40 epochs with a batch size of 32, using the Adam optimizer which was used for its adaptive learning rate and effective gradient handling. The model optimizes its weights by minimizing the Sparse Categorical Cross-Entropy loss function, which measures the difference between true labels and predicted probabilities. For a sample belonging to class c, the loss L is defined in equation 5:

$$LCE = -\sum_{i=1}^{C} yilog(yi) \tag{5}$$

3.6 Evaluation Metrics

To test the performance of the proposed LCCNN model, several evaluation measures were used. These metrics shows how accurately the model classifies Late Blight, Early Blight, and healthy classes. A confusion matrix was generated to visualize the model's predictions with the actual labels. It shows the True Positives (TP), True Negatives (TN), False Negatives (FN) and False Positives (FP), enabling the identification of specific misclassifications among similar diseases. The proposed model's performance was checked using the accuracy, recall, precision, and F1-Score.

- **Accuracy:** It shows the correctness of the model's performance.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{6}$$

- **Precision:** It measures the accuracy of the +ve predictions and shows how effectively the model reduces false positives.

$$Precision = \frac{TP}{TP+FP} \tag{7}$$

- **Recall (Sensitivity):** Measures the proportion of actual +ve correctly identified, which is critical for ensuring diseased plants are not overlooked.

$$Recall = \frac{TP}{TP+FN} \tag{8}$$

- **F1-Score:** The harmonic mean of Precision and Recall. It is mainly useful when the dataset has class imbalance.

$$F1 = 2\ .\ \frac{Precision\ .Recall}{Precision+Recall} \tag{9}$$

4. Results and Discussion:

The proposed LCCNN model was trained and evaluated on a split Potato Leaf dataset. This analysis checks how well the model is trained, how stable it is, how accurate the results are, and the ability to differentiate classes.

4.1 Learning Dynamics and Stability:

The proposed model was trained for 40 epochs, and Figure 4 presents the corresponding accuracy and loss patterns.

Accuracy: During the training period, the model rapidly achieved nearly 99% accuracy in just 15 epochs, and followed by 98.7% validation accuracy. The small difference between the two curve suggests reliable learning without overfitting.

Loss: The Sparse Categorical Cross Entropy loss decreased smoothly throughout training from a high initial value to near zero, with validation loss around 0.04. This consistent decline validates the effectiveness of the Adam optimizer in minimizing the error gradient.

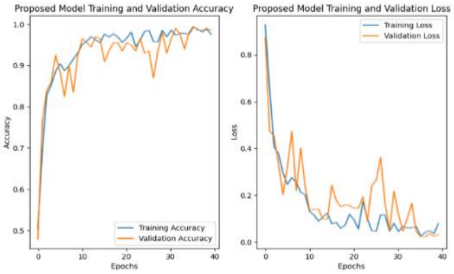

Figure 4. Accuracy and Loss Curve

4.2 Classification Performance

The model's efficiency on the unseen Testing set of 256 images was evaluated using the Confusion Matrix and class wise metrics. As illustrated in Figure 5, the model has achieved exceptional classification results across all categories:

- **Early Blight**: 112 images were correctly identified with 0 misclassifications.
- **Late Blight**: 119 images were correctly identified. Only 2 misclassifications occurred (1 predicted as Early Blight, 1 as Healthy).

- **Healthy**: All 23 healthy leaf samples were correctly classified.
  The overall testing accuracy derived from this matrix is 99.2%, achieving 254 correct predictions out of 256 samples. This states that the model is highly robust even with the reduced parameter count.

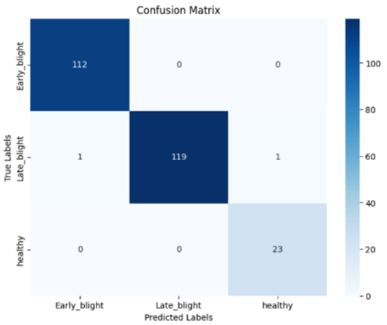

Figure 5. Confusion Matrix Analysis

To further evaluate the proposed model's efficiency, Recall, Precision, and F1-scores were calculated and compared with all four models: LCCNN, VGG16, ResNet50, and DenseNet121. As summarized in Table 2, the proposed model achieved consistently high scores across all categories, attaining perfect score of 1.00 for Healthy class, while Early Blight and late Blight reached F1-scores of 0.98 and 0.99, respectively.

To visualize these differences, Figure 6 presents a Bar Graph for Class wise performance metrics for all four models. The figure highlights the superior performance of the proposed LCCNN model compared to existing deep learning architectures.

Table 2. Class-wise Performance Metrics.

Class	Metric	LCCNN	VGG16	ResNet50	DenseNet121
Early Blight	Precision	0.99	0.97	0.98	0.96
	Recall	0.98	0.96	0.97	0.95
	F1-score	0.98	0.97	0.97	0.95
Late Blight	Precision	0.98	0.96	0.97	0.95
	Recall	0.99	0.95	0.96	0.94
	F1-score	0.99	0.95	0.96	0.94
Healthy	Precision	1	0.98	0.99	0.97
	Recall	1	0.97	0.98	0.96
	F1-score	1	0.97	0.98	0.96

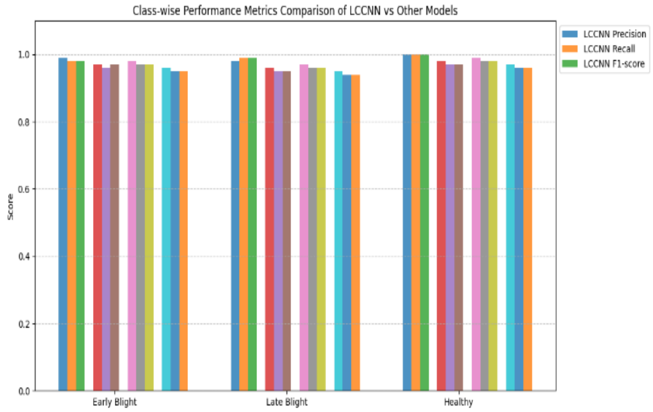

Figure 6. Bar Graph for Class-wise Performance Metrics

The performance of the proposed LCCNN model was compared to the existing heavy weight models referenced in the literature. As summarized in Table 3, our model performs superior to VGG16 and ResNet50 with significantly fewer parameters i.e. 1.9 million vs 138 million parameters. VGG16, ResNet50 and DenseNet121 requires 138 million, 25 million and 8 million parameters, respectively. Whereas the proposed model operates with approximately 1.9 million parameters, resulting in a lower model complexity and lesser memory consumption. In addition to that LCCNN shows a significantly lower latency compared to heavier architectures. As summarized in Table 3, Slow is defined as high latency of more than 500ms per sample, whereas Fast defines as average latency of less than 100ms suitable for instant field diagnosis.

For further visualization, Figure 7 presents a bar graph of parameter count and relative inference speed across the evaluated models for performance comparison. This comparison highlights the efficiency-accuracy trade-off: the LCCNN matches the predictive power of deep transfer learning models but requires a fraction of the computational memory, making it uniquely suited for mobile and edge-computing applications in agriculture

Table 3. Model Comparison Based on Parameters and Inference Speed.

Model	Parameter (Approx.)	Avg.Inference Time
VGG16	138M	Slow
ResNet50	25M	Moderate
DenseNet121	8M	Slow-Medium
Proposed LCCNN	1.9M	Fast

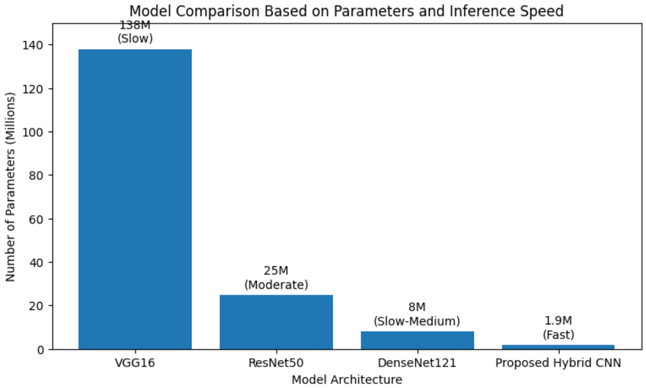

Figure 7. Bar Graph for Performance Comparison with Existing Architectures.

5. Conclusion

Potato leaf disease, specifically Early Blight and Late Blight, pose a severe threat to global food security, necessitating rapid and accurate diagnostic tools. This study presented a Lightweight Customized Convolutional Neural Network (LCCNN) designed to address the limitations of existing heavy-weight deep learning models. By optimizing the architectural depth and feature extraction process, the proposed model reduced the parameter count to approximately 1.9 million, a significant reduction compared to standard transfer learning models like VGG16 which uses approximately 138 million parameters. Experimental results on the PlantVillage dataset demonstrated the superior performance of the LCCNN, achieving a testing accuracy of 99.2%. The model exhibited exceptional discriminative capability, with Precision, Recall, and F1-scores exceeding 98% across all classes. Crucially, the reduced computational complexity ensures that the model can be effectively deployed on resource-constrained edge devices, such as smartphones and IoT-enabled drones. This research confirms that lightweight, custom-designed architectures can achieve state-of-the-art performance, providing a practical, scalable, and real-time solution for precision agriculture. While the proposed system demonstrates promising results, several avenues for future research and improvement remain. Future work will focus on integrating the LCCNN model into a user-friendly Android or iOS mobile application, enabling farmers to perform real-time, on-site disease diagnostics using smartphone cameras. Additionally, the proposed architecture can be embedded into IoT-enabled drones to support large-scale agricultural monitoring and real-time aerial surveillance of potato crops.

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