Comparative analysis of tiny machine learning models for maize crop disease identification

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ABSTRACT

This paper presents a comprehensive analysis of tiny machine-learning models for identifying maize crop diseases. The study evaluates custom deep neural network (DNN) models alongside popular deep learning architectures in terms of their effectiveness and efficiency in disease identification. The traditional crop disease detection methods such as manual checking of crop leaves for defects have become obsolete hence the need for modern and machine learning methods that are accurate and precise. This paper uses a dataset with maize crops as an example. This paper also compares four types of deep learning architectures used with custom deep learning architectures namely MobileNet, EfficientNet, ShuffleNet, and SqueezeNet. MobileNet is a lightweight CNN for mobile devices, it uses depth-wise separable convolutions for efficiency. EfficientNet is a scalable CNN architecture balancing depth, width, and resolution for optimal performance across resource-constrained devices. ShuffleNet is an optimized CNN with channel shuffle operations for cross-group information flow, ideal for resource-constrained environments. SqueezeNet is a compact CNN-based deep learning architecture utilizing fire modules to minimize parameters while preserving accuracy, it is suitable for IoT and embedded systems. The comparison of these architectures was done using the accuracy, loss, train time, and validations as the model selection criteria for comparison. The results show that MobileNet and SqueezeNet outperform both the Custom Model and ShuffleNet in terms of both test loss and test accuracy. EfficientNet, however, shows significantly poorer performance compared to the other models, particularly in terms of test accuracy. The Custom Model achieved a test loss of 0.15 with a test accuracy of .96.38%, while MobileNet attained a lower test loss of 0.098 and a higher test accuracy of 97.32%. In contrast, EfficientNet exhibited the highest test loss of 2.79 with the lowest test accuracy of 28.43%. ShuffleNet showed a test loss of 0.12 and a test accuracy of 96.18%, whereas SqueezeNet achieved a slightly lower test loss of 0.09 but a similar test accuracy of 96.84. Contribute to advancing the development of precision agriculture technologies tailored to address crop health challenges.

Keywords: CNN; deep neural network; disease identification; EfficientNet; maize crop; MobileNet; SqueezeNet; ShuffleNet; Tiny Machine Learning

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Introduction

Maize crop diseases pose significant threats to agricultural productivity worldwide. According to recent statistics, crop diseases can cause up to 40% loss in yield annually, leading to substantial economic losses and food insecurity in many regions (Savary *et al.*, 2012). Traditional methods of disease identification, such as manual inspection of crop leaves, are labor-intensive, time-consuming, and often prone to errors, rendering them inadequate for large-scale farming operations.

In response to these challenges, there has been a growing interest in leveraging machine learning techniques, particularly tiny machine learning models, for more accurate and efficient disease identification in maize crops. Tiny machine-learning models refer to lightweight and resource-efficient models optimized for deployment on edge devices with limited computational power and memory (Liu *et al.*, 2021) (Rahul Kumar *et al.*, 2022). These models hold immense potential for revolutionizing precision agriculture by enabling real-time disease detection and targeted intervention strategies.

Recent advancements in deep learning architectures, such as Convolutional Neural Networks (CNNs), have paved the way for the development of tiny machine learning models tailored specifically for agricultural applications. These models, including MobileNet, EfficientNet, ShuffleNet, and SqueezeNet, offer a promising avenue for automating the detection and diagnosis of maize crop diseases with high accuracy and reliability.

The primary objective of this paper is to conduct a comprehensive analysis of these tiny machine-learning models in the context of maize crop disease identification. By evaluating the effectiveness and efficiency of these models, we aim to provide insights into their practical applicability and performance across various agricultural settings.

Throughout this paper, we explore how these tiny machine-learning models compare in terms of accuracy, loss, training time, and validation metrics, shedding light on their suitability for real-world deployment in precision agriculture. By leveraging the power of deep learning and tiny machine learning models, we strive to contribute to the advancement of sustainable farming practices and the mitigation of crop health challenges on a global scale.Top of Form

Background and Literature Review

In agricultural research, significant efforts have been dedicated to categorizing, identifying, and delineating the attributes of plant diseases by employing deep learning methodologies and image-processing techniques. Moreover, the utilization of convolutional neural network (CNN) processing methodologies has gained momentum in the examination of plant diseases within the realm of agriculture. The research encompassed several databases, incorporating IEEE Xplore, ResearchGate, and Google Scholar. The authors employed targeted keywords like “deep learning,”, “Models”, "Maize leaf disease detection," and "TinyML" to pinpoint pertinent articles and studies. Plant diseases are the major cause of low agricultural productivity. Mostly the farmers encounter difficulties in controlling and detecting plant diseases. Thus, early detection of these diseases will be beneficial for farmers to avoid further losses. A range of machine learning and deep learning models have been explored for maize crop disease identification. Our reviewed paper referenced by (Panigrahi *et al.*, 2020) focuses on supervised machine learning techniques such as Naive Bayes (NB), Decision Tree (DT), K-Nearest Neighbor (KNN), Support Vector Machine (SVM), and Random Forest (RF) for maize plant disease detection with the help of the images of the plant. The aforementioned classification techniques are analyzed and compared to select the most suitable model with the highest accuracy for plant disease prediction. The RF algorithm results with the highest accuracy of 79.23% as compared to the rest of the classification techniques. All the aforesaid trained models will be used by the farmers for the early detection and classification of the new image diseases as a preventive measure.

The investigation of transfer learning of deep convolutional neural network and modification of the network structure to improve the learning capability of pant lesion characteristic was done by (J. Chen *et al.*, 2021) The MobileNet with squeeze-and-excitation (SE) block was selected in our approach. Integrating the merits of both, the pre-trained MobileNet and SE block were fused to form a new network, which we termed the SE-MobileNet, and was used to identify the plant diseases. In particular, the transfer learning was performed twice to obtain the optimum model. The first phase trained the model for the extended layers while the bottom convolution layers were frozen with the pre-trained weights on ImageNet; by loading the model trained in the first phase, the second phase retrained the model using the target dataset. The proposed procedure provides a significant increase in efficiency relative to other state-of-the-art methods. It reaches an average accuracy of 99.78% in the public dataset with clear backdrops. Even under multiple classes and heterogeneous background conditions, the average accuracy is 99.33% for identifying the rice disease types. The experimental findings show the feasibility and effectiveness of the proposed procedure.

Another paper we reviewed referenced as (Nourish *et al.*, 2023) provided a comprehensive review of deep learning methods for plant disease identification, emphasizing the need for further research to improve system performance and accuracy. Their main objective was to strengthen the quality of maize plant leaf disease detection and inspire further research in this field. The process of detecting and recognizing disease in plants is crucial for the early control of pests and diseases that significantly affect plant growth. Although maize is the most productive food crop worldwide, it can suffer from physiological lesions caused by viral and fungal infections primarily visible in the leaves. The automatic identification and classification of plant diseases are essential for sustainable agriculture, but it remains a significant challenge. Existing techniques proposed for this purpose are limited in scope and rely solely on models for deep learning. Using cropped photos, convolutional neural networks have been demonstrated to be the most adequate method for identifying and forecasting illnesses. An overview of deep learning methods for identifying plant diseases is given in this article, which also includes data collection sources, deep learning architectures, and image processing methods. The study evaluates existing deep learning models and highlights their results, with a focus on future research to improve system performance and accuracy for detecting crop diseases using better deep learning capabilities.

The timely identification and early prevention of crop diseases are essential for improving production and were examined by researchers to identify and diagnose diseases in plants from their leaves since CNNs have achieved impressive results in the field of machine vision. Standard CNN models require a large number of parameters and higher computation costs. (Hassan *et al.*, 2021) In this paper, we replaced standard convolution with depth=separable convolution, which reduces the parameter number and computation cost. The implemented models were trained with an open dataset consisting of 14 different plant species, 38 different categorical disease classes, and healthy plant leaves. To evaluate the performance of the models, different parameters such as batch size, dropout, and different numbers of epochs were incorporated. The implemented models achieved disease-classification accuracy rates of 98.42%, 99.11%, 97.02%, and 99.56% using InceptionV3, InceptionResNetV2, MobileNetV2, and EfficientNetB0, respectively, which were greater than that of traditional handcrafted-feature-based approaches. In comparison with other deep-learning models, the implemented model achieved better performance in terms of accuracy and it required less training time. Moreover, the MobileNetV2 architecture is compatible with mobile devices using the optimized parameter. The accuracy results in the identification of diseases showed that the deep CNN model is promising and can greatly impact the efficient identification of diseases, and may have potential in the detection of diseases in real-time agricultural systems.

These studies collectively highlight the potential of various machine learning and deep learning models for maize crop disease identification, with models showing particularly promising results but each of the researchers did not focus their model development on resource-constrained devices with low Random Access Memory, low flash size, and low memories. The Summary of some notable related works is tabulated in Table 1 below.

Materials and Methods

In the realm of agricultural technology, the identification of maize crop diseases stands as a crucial endeavor. As traditional methods of disease detection become outdated, the integration of modern machine learning techniques offers a promising solution. This paper undertakes a comparative analysis of tiny machine-learning models tailored for the identification of maize crop diseases. By evaluating the effectiveness and efficiency of these models, we aim to discern optimal methodologies for disease identification in agricultural settings. Through the exploration of deep learning architectures such as

MobileNet, EfficientNet, ShuffleNet, and SqueezeNet, we seek to shed light on their performance and potential contributions to precision agriculture technologies.

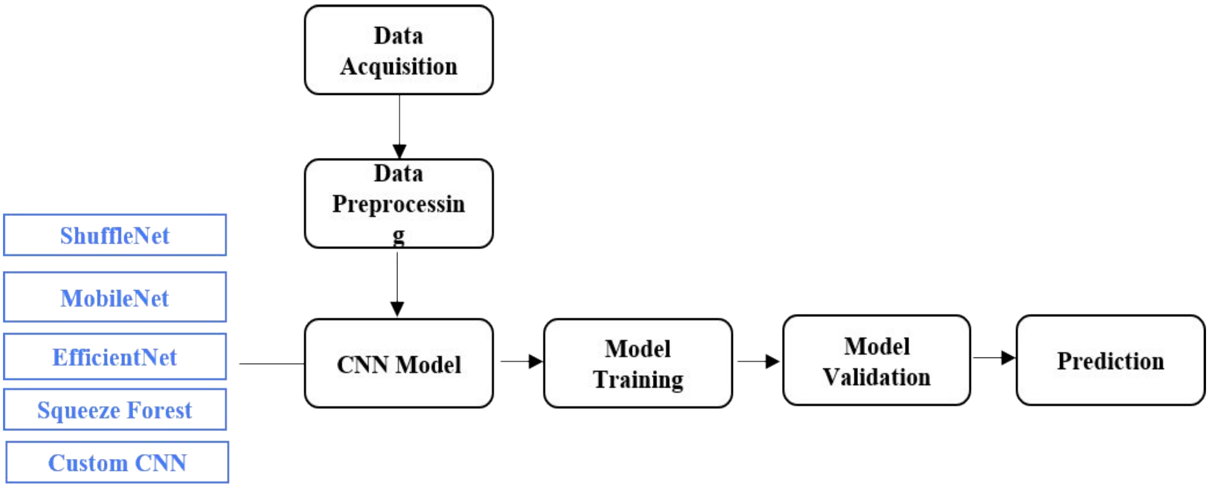

Fig 1: Workflow for this project.

TABLE 1
Summary of some Notable works

References	Learning Model	Dataset	Type Classification	Performance	Limitations
Chen, J., *et al.* (2021) [1]	Squeeze-and-excitation MobileNet model, twice transfer learning	Apple Leaf Dataset from Kaggle and Field Shooting	Plant disease identification	The average accuracy of 99.78% in a public dataset, 99.33% for rice disease types	Higher Error rate in identifying disease types with smaller lesions.
Hassan, S. M., *et al.* (2021) [2]	InceptionV3, InceptionResNetV2, MobileNetV2, EfficientNetB0	Open dataset with 14 plant species, 38 disease classes, and healthy leaves from PlantVillage Dataset	Plant Disease classification	The model achieved 98.42%, 99.11%, 97.02%, and 99.56% accuracy rates, respectively	The work has limited analysis of the implementation of Resource-constrained devices
Liu, Y., *et al.* (2021) [3]	Improved SqueezeNet model	Self-provided dataset of granular crops represented by peanuts	Grain crop image classification	Their accuracy rate of the training test set as 94.4%,	The work was limited to granular crops.

Nourish, A., *et al.* (2023) [4]	Deep learning models	Used PlantVillage Dataset	Maize leaf disease detection and classification	N/A	Emphasized the need for further research to improve system performance and accuracy, standardized datasets, and lack of comparative studies
Panigrahi, K. P., *et al.* (2020) [5]	Naive Bayes, Decision Tree, K-Nearest Neighbor, Support Vector Machine, Random Forest	PlantVillage Dataset	Maize plant disease detection	The Random Forest algorithm resulted in the highest accuracy of 79.23%	Relatively models recorded less than 80% accuracy. Which can be improved.

Dataset Collection

The dataset utilized in this study encompasses a diverse array of categories crucial to agricultural research, including Blight, Common Rust, Gray Leaf Spot, Streak Virus, and Healthy leaves. Sourced meticulously from reputable repositories such as Kaggle, Harvard Dataverse (Mduma, Neema, *et al.* 2022), and Mendeley Data (Mensah Kwabena, Patrick, *et al.* 2023), these high-quality images ensure the authenticity and relevance required for robust analysis. Originally, the images within the dataset exhibited varying dimensions and were provided in JPEG format. To facilitate streamlined analysis and ensure uniformity, augmented images were incorporated, each resized to a standardized dimension of 96×96 pixels. This preprocessing step maintains data integrity and simplifies the research process by providing consistent inputs for model training and evaluation.

The dataset used in this study consists of a combined set of raw images, totaling 12,344 instances, and augmented images, amounting to 7,454 color images. To partition the dataset for model training and evaluation, a standard practice of splitting into training and testing sets was employed. The split ratio of 80/20, determined through empirical studies, ensures an optimal balance between model training and evaluation performance. The dataset distribution across different classes is as follows: Blight (4,099 images), Common Rust (3,480 images), Gray leaf Spot (4,159 images), Healthy (3,948 images), and Streak Virus (4,109 images). This distribution is visualized graphically in Fig. 3, providing insights into the distributional characteristics of the dataset across various classes. Additionally, Fig. 4 offers a visual representation of each class, further enhancing the understanding of the dataset's composition and diversity.

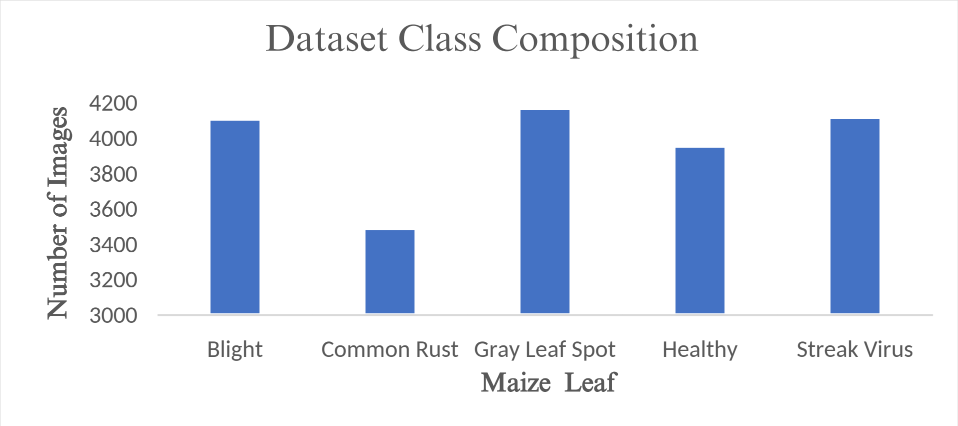

Fig 2: Dataset image class count

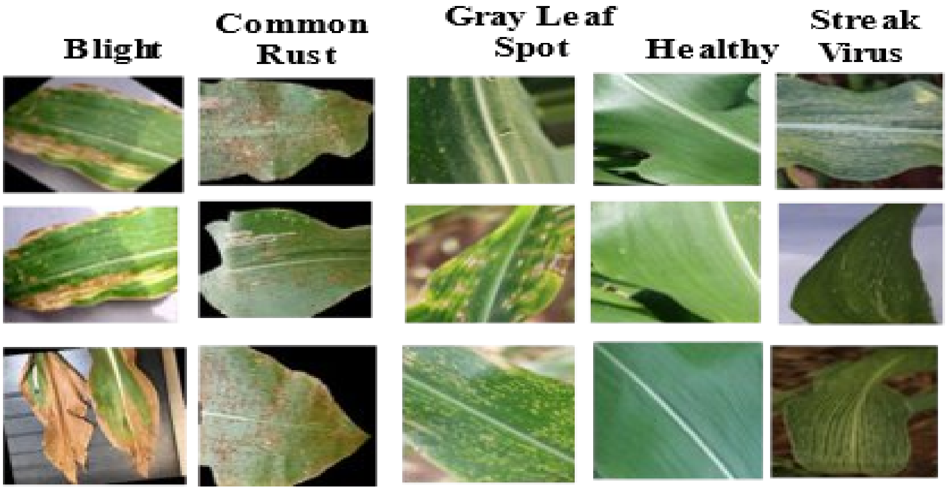

Fig 3: Dataset Image Class Samples

Overall, this extensive dataset serves as a valuable resource for researchers, agricultural experts, and machine learning practitioners, fostering advancements in disease detection and classification in maize crops. Its comprehensive nature and meticulous curation contribute to the development of robust and accurate machine-learning models tailored to address real-world agricultural challenges.

Top of Form

Dataset Preprocessing

Dataset preprocessing is a fundamental step in readying data for machine learning tasks, ensuring data is structured optimally for model training and evaluation. In the context of image classification and our study, our preprocessing involved several key stages:

- Loading Data: The dataset, comprising images and corresponding labels, is loaded into memory. This process can vary based on the dataset format, including loading images from directories or structured data files.
- Resizing Images: Images are often resized to a consistent dimension to ensure uniformity and compatibility with the model architecture. For instance, in the provided scenario, images are resized to dimensions of (96, 96) pixels.
- Data Augmentation: Data augmentation techniques are applied to enhance the dataset's diversity artificially. This practice aids in improving model generalization and mitigating overfitting. Common augmentation methods include random flips, rotations, zooms, shifts, and adjustments in brightness or contrast. The implementation in the provided example involves a sequence of random augmentation layers, structured using tf. keras.Sequential.

- Normalization: Pixel values within images are normalized to fall within a standardized range, often between 0 and 1. Normalization stabilizes the training process and can expedite convergence.
- Dataset Splitting: The dataset is divided into training and validation subsets, usually adhering to an 80/20 split ratio. The training subset is utilized to train the model, while the validation subset is leveraged to assess the model's performance during training and fine-tune hyperparameters.
- Batching: Data is segmented into batches of predetermined sizes. Batching optimizes memory utilization and enables parallel processing during model training.
- Class Label Encoding: Class labels are encoded into numerical formats, typically employing one-hot encoding techniques. This encoding simplifies model training and evaluation procedures.

Models Selection and Optimization

Recent advancements in image classification primarily rely on Convolutional Neural Networks (CNNs), designed to automatically detect and recognize patterns within input images. CNNs, such as ShuffleNet, EfficientNet, MobileNet, and SqueezeNet, are notable for their efficiency on resource-constrained devices. While ShuffleNet employs channel shuffling and pointwise group convolutions to achieve high performance with lower computational costs, SqueezeNet utilizes fire modules to maintain accuracy in a compact network design, ideal for edge devices.(Arun & Viknesh, 2022) EfficientNet employs compound scaling for balanced model depth, width, and resolution, optimizing performance across various computational budgets.

Meanwhile, MobileNet utilizes depthwise separable convolutions to reduce computational complexity while maintaining expressive power, making it ideal for mobile and embedded vision applications. (Dey *et al.*, n.d.) For this project, four TinyML CNN-based architectures and a custom CNN architecture were used due to their suitability for the resource-constrained microcontroller units. The CNN architectures comprise convolutional layers with a kernel size of 3 each, followed by max-pooling layers, a flattened layer, a dense layer with 128 neurons, and a dropout rate of 0.25. The model's input layer consists of 27,648 features, with the output layer containing five classes including; Blight, Common Rust, Gray Leaf Spot, Streak Virus, and Healthy. The models incorporate ReLU activation functions in their convolutional layers to introduce non-linearity and facilitate learning complex representations. To prevent overfitting, a dropout layer with a dropout rate of 0.25 is added after the densely connected layer with 128 units.

Additionally, L1 regularization is applied to the dense layer to control overfitting by penalizing the loss function. Hyperparameters play a crucial role in shaping the behavior and effectiveness of deep learning algorithms. For this research, the following hyperparameters were refined and adjusted: Following model optimizations, notable improvements were observed across various metrics, including reduced latency, optimized memory consumption, and maintained high accuracy. (C. Chen *et al.*, 2021). These enhancements underscore the model's suitability for deployment on the Arduino BLE Sense platform. The optimized hyperparameter values used for the model are summarized in Table 2:

TABLE 2

General Models Hyperparameters

Hyperparameter	**Value**
Learning Rate	0.0005
Batch Size	32
Epochs	20
Dropout Rate	0.25
Beta1	0.9
Beta2	0.99

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Deep Learning Models

Each selected model architecture underwent rigorous examination and customization to ensure optimal performance in maize crop disease identification: Detailed architectural diagrams and model summaries were created for MobileNet, EfficientNet, ShuffleNet, SqueezeNet, and the Custom CNN model. Equations and formulae were employed to elucidate specific components and operations within each architecture, providing insights into their design principles and computational efficiency.

ShuffleNet

ShuffleNet presents a highly efficient convolutional neural network (CNN) architecture specifically tailored for mobile devices with limited computational power, ranging from 10-150 Million Floating Operating Per Second (MFLOPs). ShuffleNet integrates novel techniques like pointwise group convolution and channel shuffle to reduce computation costs while maintaining accuracy drastically. By enabling information flow across feature channels and leveraging group convolutions, the ShuffleNet model is designed for image classification tasks. (Zhang *et al.*, 2017) It comprised three convolutional layers followed by max-pooling layers to extract features and reduce spatial dimensions. A flattened layer transforms the output into a one-dimensional vector, facilitating input to fully connected layers.(Wijaya *et al.*, 2022) The model includes a dense layer with 128 units for feature extraction and a dropout layer to prevent overfitting. The final dense layer, with five units, serves as the output layer for classification. This architecture is well-suited for tasks requiring image classification, such as identifying diseases in maize crops. Fig 4. Shows the architecture of our ShuffleNet model.

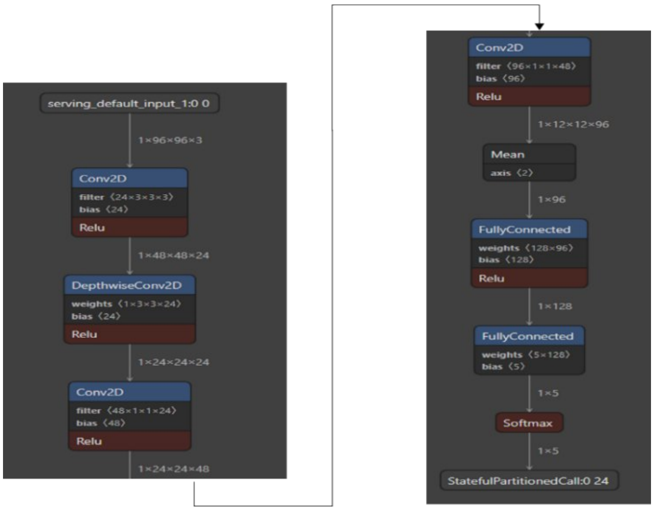

Fig 4: Our ShuffleNet Architecture

EfficientNet

EfficientNet is a scalable convolutional neural network architecture that balances depth, width, and resolution to achieve optimal performance across resource constraints. (Yi *et al.*, 2022) The provided architecture represents EfficientNet, a scalable convolutional neural network designed to balance model complexity and computational efficiency. It consists of multiple blocks, each containing depthwise convolutions, batch normalization, and activation layers. The network starts with a stem convolution layer followed by a series of blocks with expanding and depthwise convolution operations. (Kaur *et al.*, 2023) These blocks are interconnected, allowing for feature extraction across different levels of abstraction. Additionally, squeeze-and-excite modules enhance channel-wise feature recalibration to improve model performance. The network concludes with a top convolutional layer and global average pooling to aggregate features, followed by fully connected layers for classification. Dropout regularization is applied to mitigate overfitting, and the final dense layer produces class predictions. *(Aggarwal et al.*, 2023) EfficientNet's design principles enable it to achieve high accuracy while being computationally efficient, making it suitable for various image classification tasks, including maize crop disease identification. Fig 5. Shows the architecture of our EfficientNet model.

Fig 5: Our EfficientNet Architecture

MobileNet

We used an architecture that outlines MobileNet, a lightweight convolutional neural network designed for mobile and embedded devices. (Howard *et al.*, 2017) It consists of multiple layers, starting with an input layer accepting images of size 96x96x3. The network incorporates depthwise separable convolutions, which significantly reduce computational complexity by separating spatial and depthwise convolutions. Batch normalization and ReLU activation functions are applied after each convolutional layer to stabilize and enhance the learning process. The network architecture includes several blocks of depthwise and pointwise convolution layers, progressively reducing spatial dimensions while increasing the number of channels. Global average pooling is employed to condense spatial information into a feature vector, which is then passed through fully connected layers for classification. (Howard *et al.*, 2017) Dropout regularization is used to prevent overfitting, and the final dense layer produces class predictions. MobileNet's architecture prioritizes efficiency and performance, making it suitable for resource-constrained environments and applications like maize crop disease identification. Fig 6. Shows the architecture of our MobileNet model.

Fig 6: Our MobileNet Architecture

SqueezeNet

The used architecture depicts SqueezeNet, a compact convolutional neural network designed to achieve high accuracy with significantly fewer parameters than traditional architectures. It begins with an input layer accepting images of size 96x96x3. (Iandola *et al.*, 2016) The network primarily consists of convolutional layers, with occasional max-pooling layers for downsampling. SqueezeNet employs a fire module architecture, which comprises a combination of 1x1 pointwise convolutions to reduce the number of input channels followed by a mix of 1x1 and 3x3 convolutions to capture spatial information effectively. These fire modules are concatenated to form the network's backbone, enabling efficient feature extraction. Dropout layers are inserted to mitigate overfitting during training. (Hidayatuloh *et al.*, n.d.) The final layers include a convolutional layer with a 3x3 kernel to produce the output logits, followed by global average pooling to condense spatial information into a vector. An activation function (such as softmax) is applied to produce the final class probabilities. SqueezeNet's design emphasizes parameter efficiency and computational speed, making it suitable for resource-constrained environments and applications like maize crop disease identification. (Safie *et al.*, 2023) Fig 7. Shows the architecture of our SqueezeNet model.

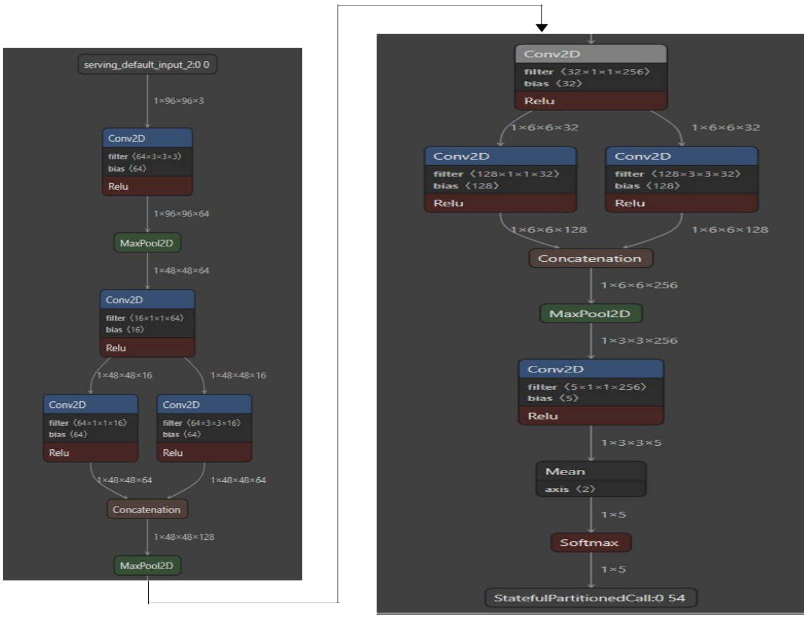

Fig 7: Our MobileNet Architecture

Custom Model

Our custom model architecture comprised a series of convolutional (Conv2D) and max-pooling (MaxPooling2D) layers followed by a flattened layer to transition from convolutional to fully connected layers. The convolutional layers employ varying filter sizes and numbers to extract hierarchical features from the input data, which are then downsampled using max-pooling operations to reduce spatial dimensions while preserving important features. (J. Chen & Ran, 2019). The flattened layer reshapes the output from the convolutional layers into a vector suitable for input into the subsequent fully connected layers. The dense layers (Dense) serve as the classifier, with the final layer (y_pred) producing the model's output predictions. A dropout layer is included to prevent overfitting by randomly dropping connections during training. (Nourish *et al.*, 2023) This architecture is designed for classification tasks, particularly for maize crop disease identification, where the model learns to classify images into one of five classes based on the features extracted from the input images. Fig 8. Shows the architecture of our Custom model.

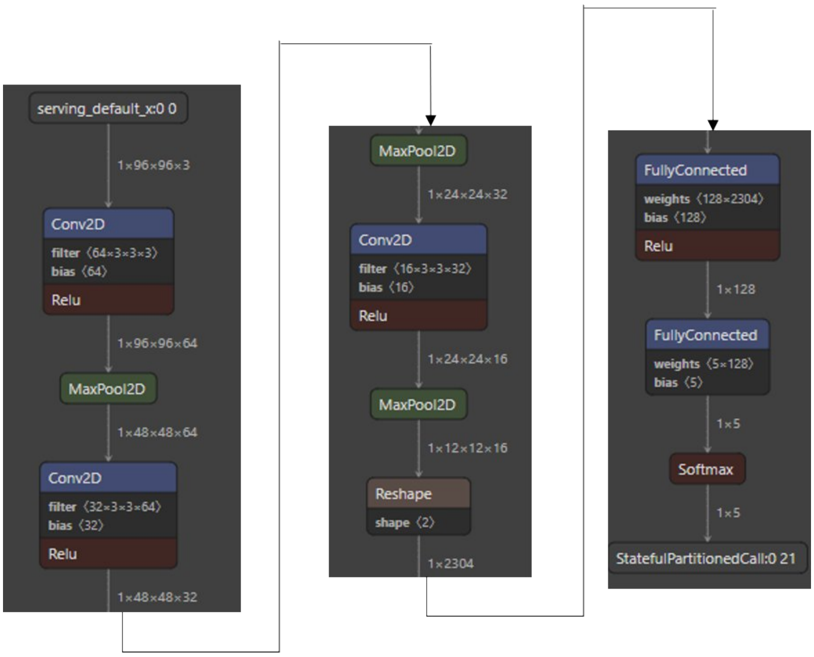

Fig 8: Custom Model Architecture

Comparison of the Models

The performance evaluation of each model was conducted systematically, we employed a comprehensive array of evaluation metrics such as accuracy, loss, training time RAM size, and number of parameters. Through meticulous analysis and comparison across all models, particular emphasis was placed on several key aspects. (Da Silva *et al.*, 2023) Loss metrics were scrutinized to gauge the optimization objectives during model training, reflecting the disparity between predicted and ground-truth labels. (Tan & Le, 2019)Moreover, the training time, indicative of the computational resources and duration required for each model to reach convergence, was thoroughly examined. The comparison analysis aimed to discern the strengths and limitations of each model in the context of maize crop disease identification. Insights gleaned from this comprehensive comparison process served to inform the selection of the most effective and efficient model for real-world deployment in precision agriculture applications.

Results and Discussion

In this section, we present the experimental results obtained from the evaluation of various models designed for maize crop disease identification. The experiments were meticulously conducted, utilizing a diverse range of evaluation metrics including accuracy, loss, and training time. The objective of our study was to assess the performance of each model and compare their efficacy in accurately classifying maize crop diseases while differentiating them from healthy plants. (Yumang *et al.*, 2023) Through systematic analysis and comparison of the experimental outcomes, we aimed to identify the strengths and limitations of each model, ultimately seeking to determine the most effective and efficient model for deployment in precision agriculture applications. The experimental results provide valuable insights into the performance of different models, offering guidance for the selection of optimal solutions in the context of maize crop disease identification.

ShuffleNet

ShuffleNet from Fig. 6 and Fig. 7 demonstrated commendable performance in maize crop disease identification, achieving a training accuracy of 97.05% and a competitive validation accuracy of 93.42%. Its test accuracy of 93.45% underscores its ability to generalize well to unseen data. Moreover, ShuffleNet exhibits efficient training, with a relatively short training time of 2,220.31 seconds. These results position ShuffleNet as a promising model for real-world deployment in precision agriculture applications due to its balance of accuracy and computational efficiency.

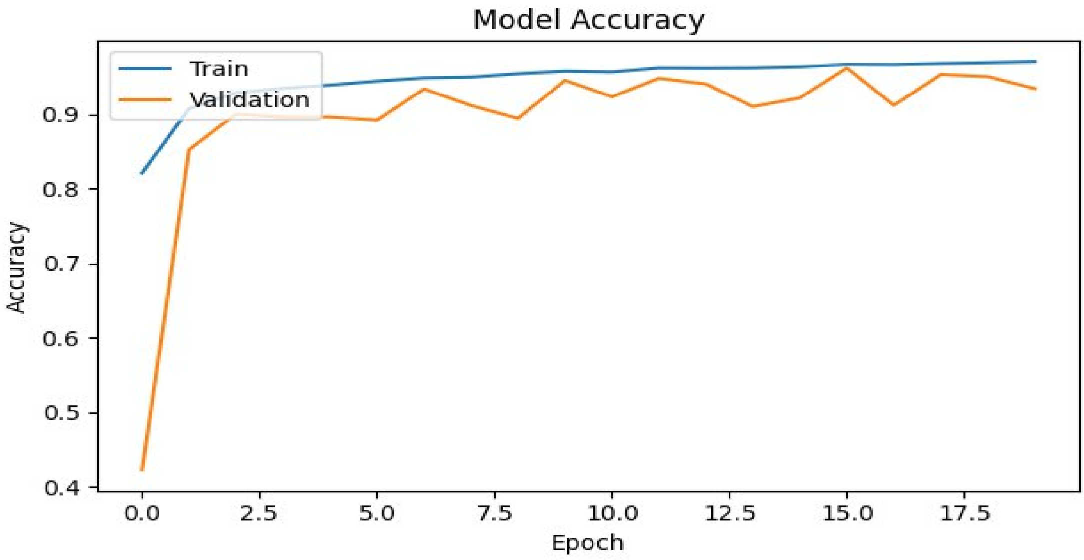

Fig 9: ShuffleNet Model training and validation accuracy

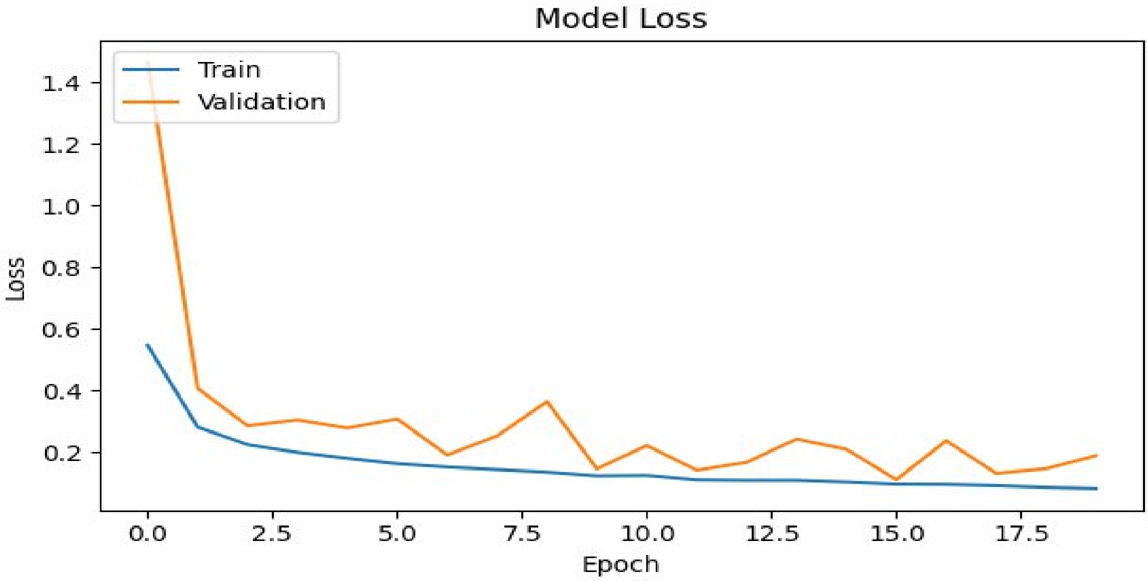

Fig 10: ShuffleNet Model training and validation loss

EfficientNet

EfficientNet achieves an impressive training accuracy of 99.45%, and its validation accuracy of 22.26% raises concerns about its ability to generalize effectively to new data. This discrepancy suggests potential overfitting issues, which are further supported by its relatively high test loss and low test accuracy of 22.33%. Additionally, EfficientNet requires a substantially longer training time of 16,726.78 seconds, highlighting its computational demands. Despite its high training accuracy, EfficientNet may not be the optimal choice for maize crop disease identification due to its poor performance on unseen data and high computational requirements. Fig 8 and Fig 9, represent the above metrics.

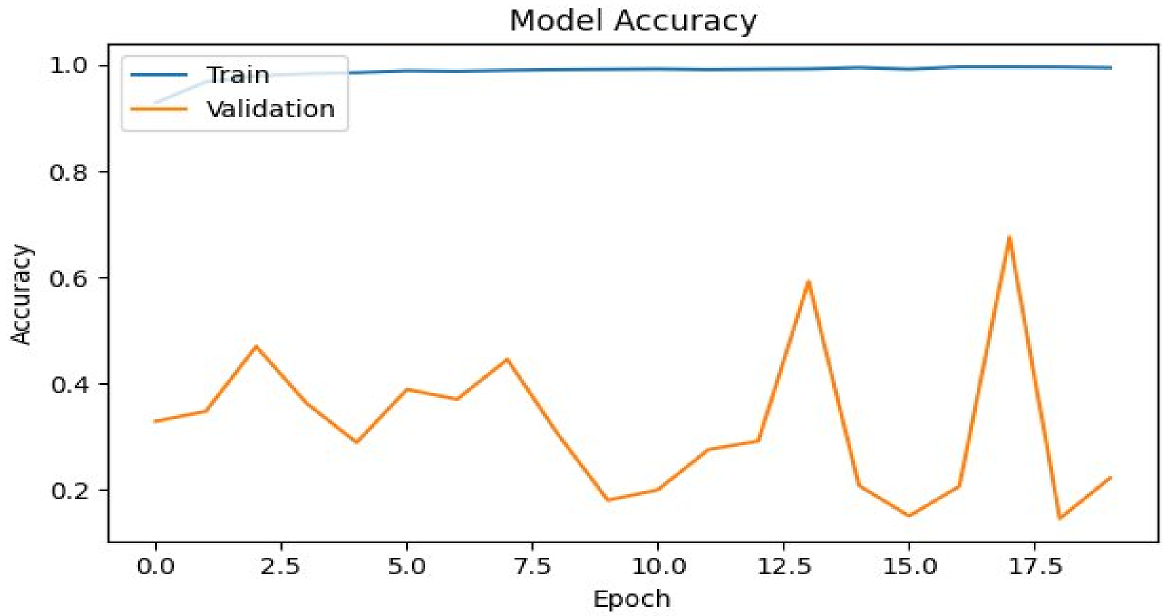

Fig 11: EfficientNet Model training and validation accuracy

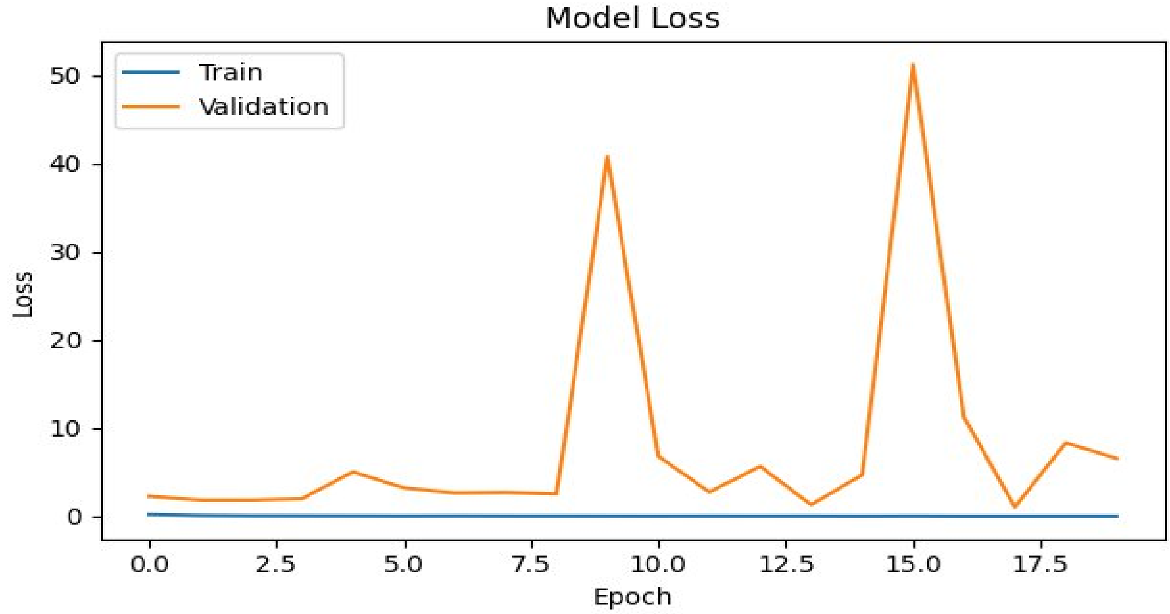

Fig 12: EfficientNet Model training and validation loss

MobileNet

MobileNet exhibits strong performance across various metrics, achieving a training accuracy of 99.39% and a validation accuracy of 98.45%. Its test accuracy of 98.46% confirms its robustness in accurately classifying maize crop diseases. With a training time of 11,192.14 seconds, MobileNet strikes a balance between accuracy and training efficiency. These results position MobileNet as a highly effective model for maize crop disease identification, suitable for real-world deployment in precision agriculture applications. Fig 10 and Fig 11, represent the above metrics.

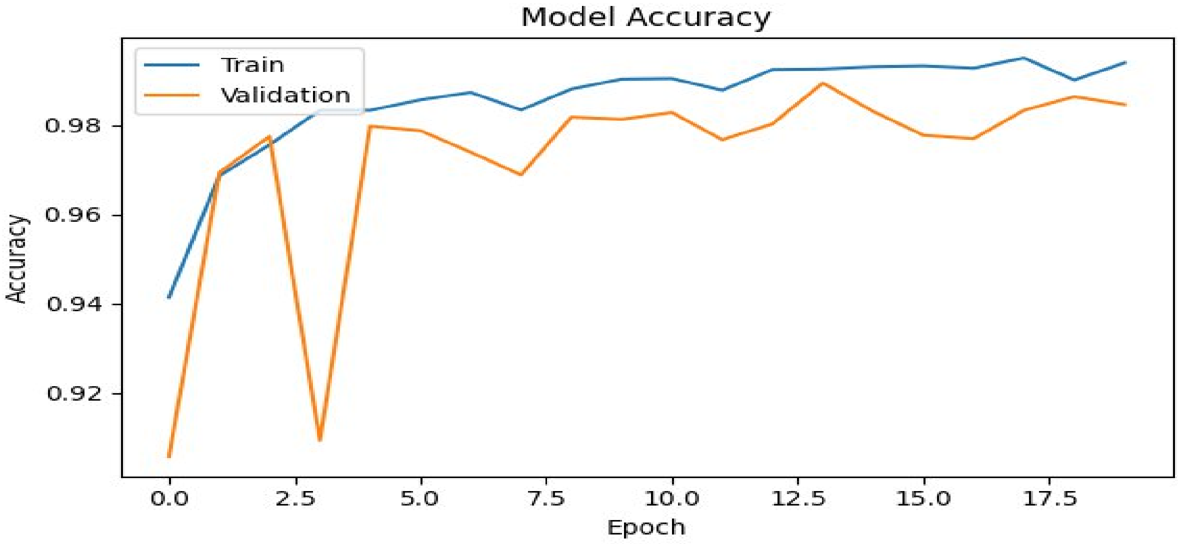

Fig 13: MobileNet Model training and validation accuracy

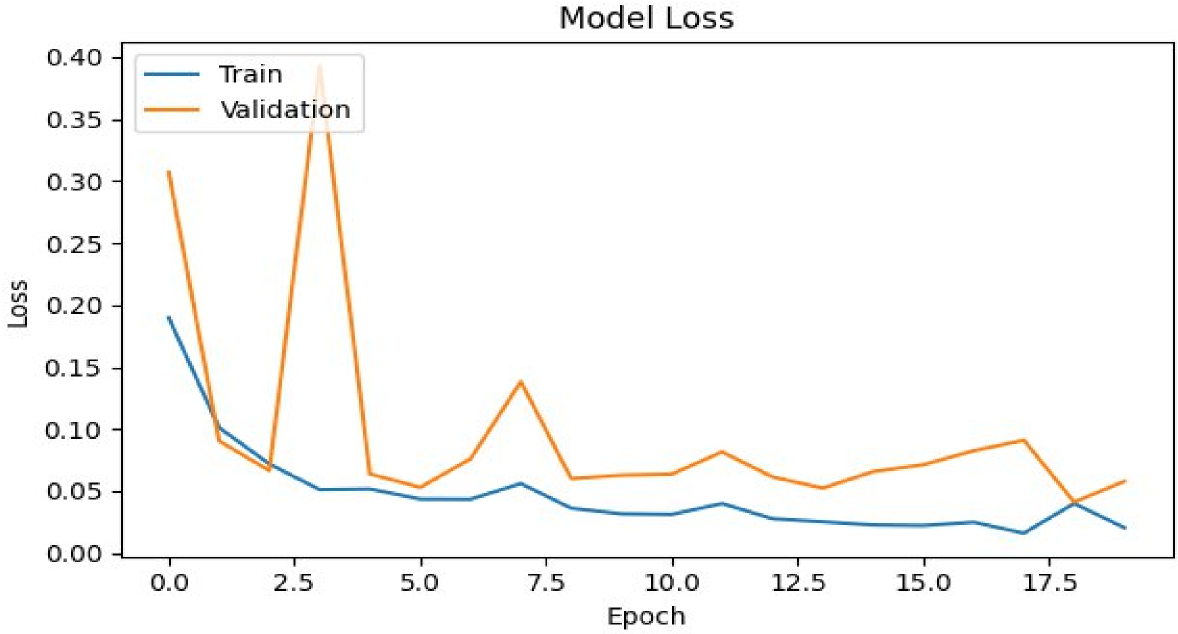

Fig 14: MobileNet Model training and validation loss

SqueezeNet

SqueezeNet demonstrates competitive performance with a training accuracy of 96.58% and a validation accuracy of 96.32%. Its test accuracy of 96.31% reflects its ability to generalize well to unseen data, supported by its relatively low test loss. SqueezeNet's training time of 5,205.79 seconds further enhances its appeal as an efficient model for maize crop disease identification. The model's combination of accuracy and training efficiency makes it a compelling choice for deployment in precision agriculture scenarios. Fig 12 and Fig 13, represent the above metrics.

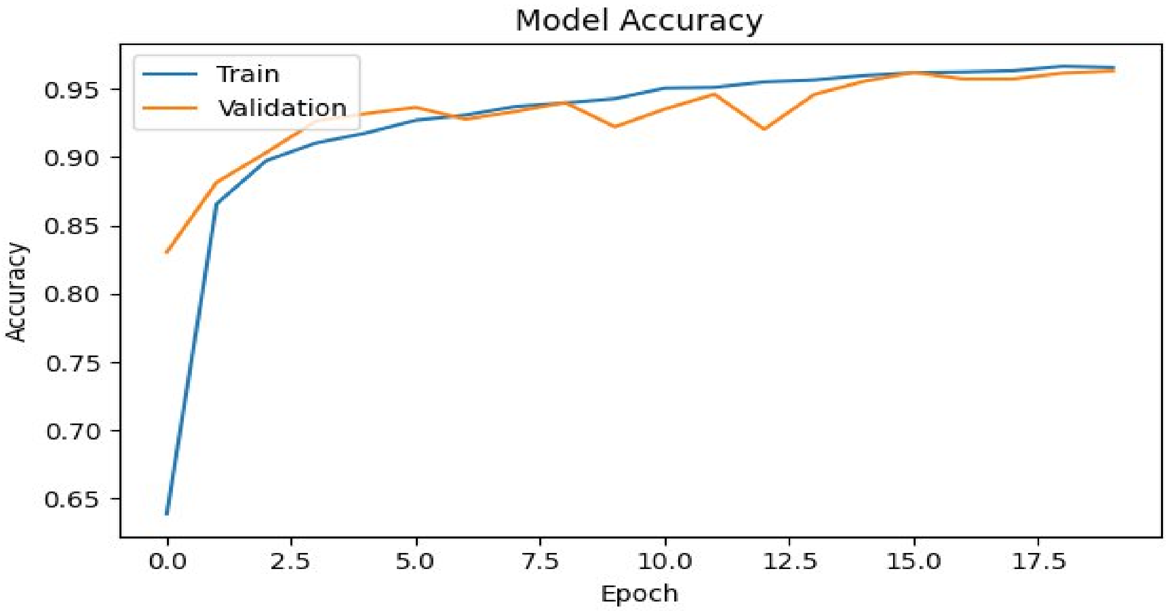

Fig 15: SqueezeNet Model training and validation accuracy

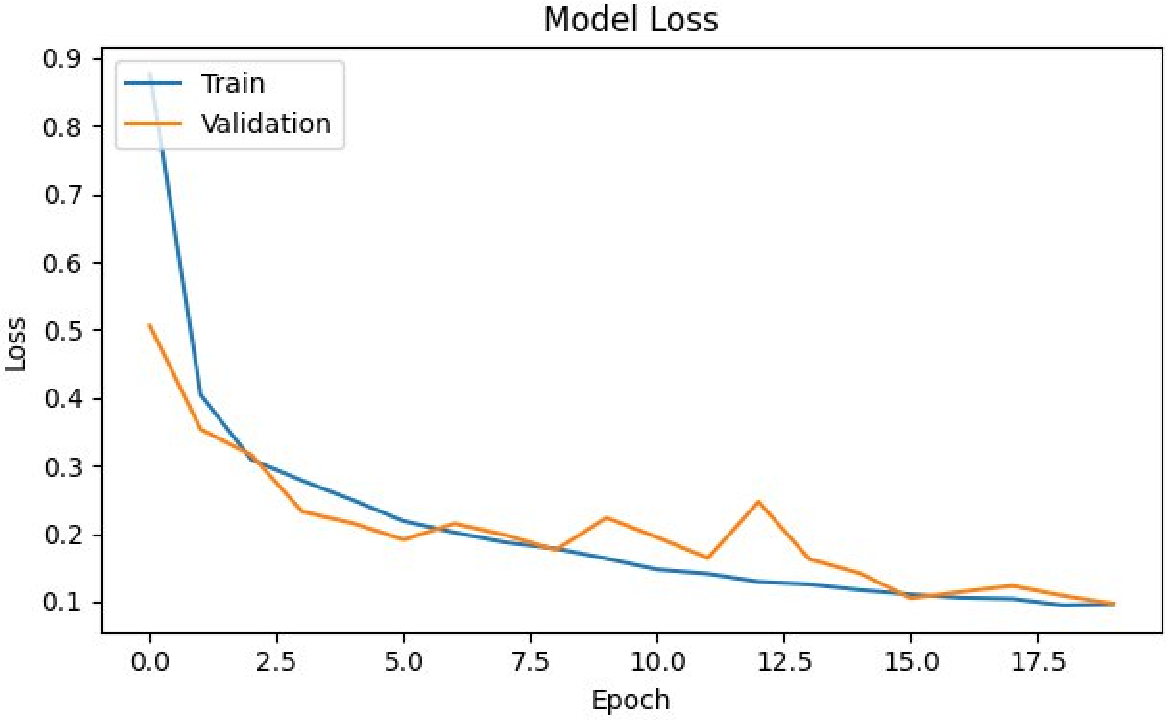

Fig 16: Squeeze Model training and validation loss

Custom Model

The custom model achieves a commendable training accuracy of 99.11% and a validation accuracy of 96.37%, reflecting its ability to generalize effectively to new data. Its test accuracy of 96.36% further corroborates its robust performance in maize crop disease identification. With a training time of 5,128.75 seconds, the custom model offers a balanced trade-off between accuracy and computational efficiency. These results highlight the efficacy of the custom model in accurately classifying maize crop diseases, making it a strong contender for real-world deployment in precision agriculture applications. Fig 14 and Fig 15, represent the above metrics.

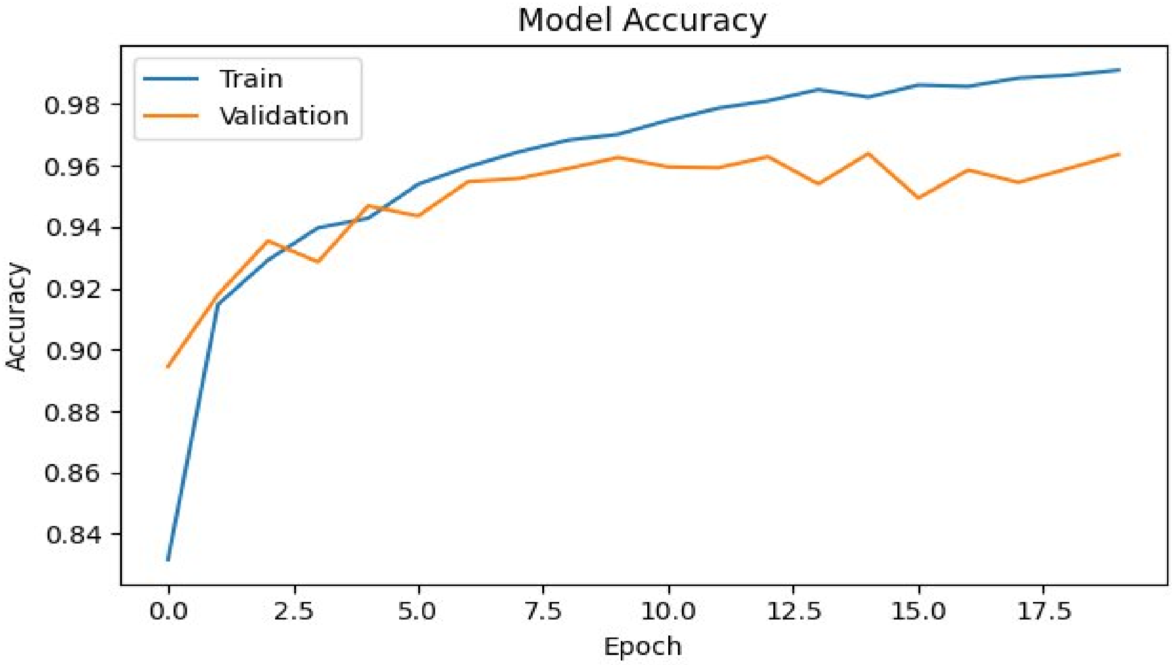

Fig 17: Custom Model training and validation accuracy

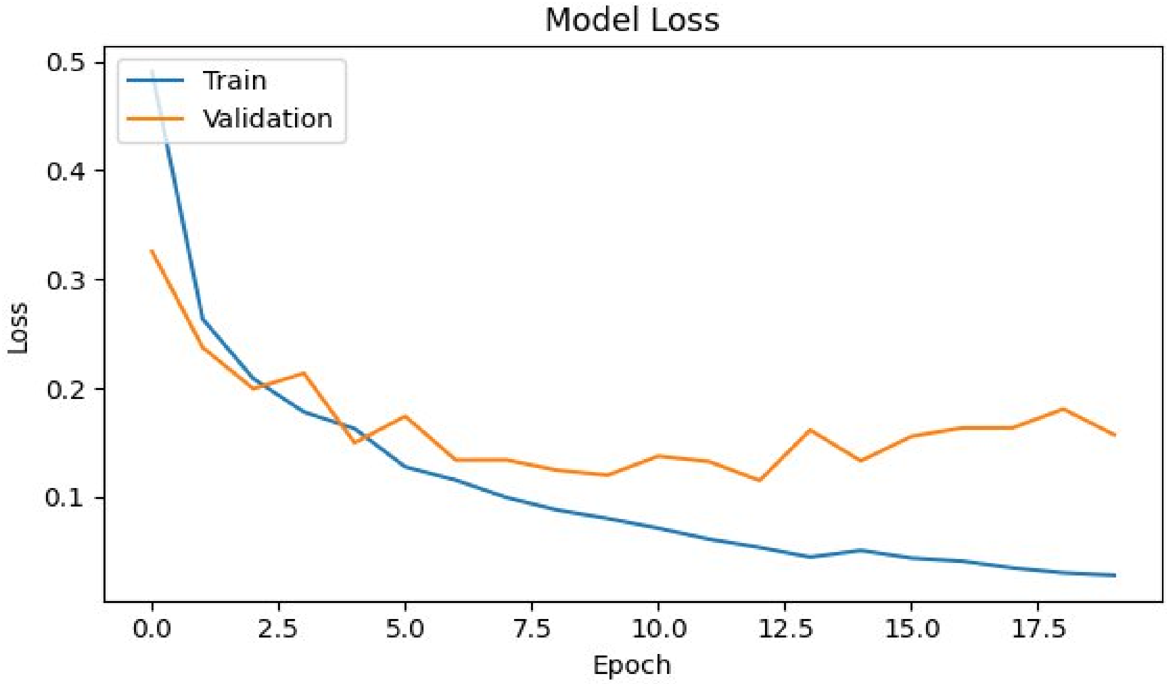

Fig 18: Custom Model training and validation loss

This table summarizes the key metrics for each model, including training accuracy, validation accuracy, validation loss, test loss, test accuracy, training time, total parameters, trainable parameters, non-trainable parameters, and model size.

TABLE 3

Summary of key metrics for each model

Model	**Training Acc**	**Validation Acc**	**Validation Loss**	**Test Loss**	**Test Acc**	**Training Time (s)**	**Total Params**	**Trainable Params**	**Non-trainable Params**	**Model Size**
ShuffleNet	0.9705	0.9342	0.1875	0.1868	0.9345	2220.31	320,565	320,565	0	85.00KB
EfficientNet	0.9945	0.2226	6.5780	6.5721	0.2233	16726.78	4,214,184	4,172,161	42,023	15.90MB
MobileNet	0.9939	0.9845	0.0580	0.0577	0.9846	11192.14	3,360,709	3,338,821	21,888	12.70MB
SqueezeNet	0.9658	0.9632	0.0968	0.0968	0.9631	5205.79	121,701	121,701	0	484.00KB
Custom Model	0.9911	0.9637	0.1574	0.1570	0.9636	5128.75	320,565	320,565	0	1.22MB

The experimental results present a comprehensive comparison of five machine learning models for maize crop disease identification: ShuffleNet, EfficientNet, MobileNet, SqueezeNet, and a custom model. Each model achieved varying levels of training accuracy, with EfficientNet leading at 99.45%, followed closely by MobileNet and the custom model at 99.39% and 99.11%, respectively. However, significant disparities emerged in validation accuracy, with ShuffleNet and MobileNet excelling at 93.42% and 98.45%, while EfficientNet and the custom model lagged at 22.26% and 96.37%. SqueezeNet also performed well with a validation accuracy of 96.32%. Regarding training time, EfficientNet required the longest duration at 16,726.78 seconds, while ShuffleNet demanded the least time at 2,220.31 seconds. Notably, while EfficientNet boasted the highest training accuracy, its validation and test accuracies were notably lower compared to MobileNet and the custom model, indicating potential overfitting concerns. Conversely, ShuffleNet demonstrated a balance of accuracy and efficiency. Based on the results, MobileNet and the custom model appear to perform the best due to their high accuracy and reasonable training times. To build a better model, one could explore ensemble methods combining the strengths of different architectures or employ transfer learning techniques to leverage pre-trained models on larger datasets for improved generalization. Additionally, fine-tuning hyperparameters and architectural modifications could enhance model performance and robustness.

Conclusion and Recommendation

The paper presents a comprehensive investigation into the application of tiny machine learning models for the identification of maize crop diseases, juxtaposing custom deep neural network (DNN) architectures with established models such as MobileNet, EfficientNet, ShuffleNet, and SqueezeNet. It underscores the limitations of conventional manual disease detection methods while highlighting the transformative potential of machine learning models in precision agriculture. Through meticulous evaluation based on metrics including accuracy, loss, training time, and validation, the study identifies MobileNet, Custom model, and SqueezeNet as standout performers among the models assessed. This emphasizes the pivotal role of such technologies in augmenting agricultural efficiency and productivity, paving the way for future advancements in precision agriculture technology. For future investigations, the paper advocates for the exploration of ensemble methods, the utilization of transfer learning techniques, and the fine-tuning of hyperparameters to elevate model performance and bolster its robustness in disease identification tasks. By delving into these avenues, researchers can further refine the efficacy and applicability of machine learning models in addressing the intricate challenges of disease detection in agriculture, thereby advancing the frontiers of precision agriculture technology.

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