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Research Article

Optimizing Plant Disease Detection Models for RISC Architectures with Mini TensorFlow

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ABSTRACT

Global agricultural productivity is a challenge to plant diseases, generating strong demand for rapid and efficient diagnostic tools for early detection and effective management. For plant disease classification, this study evaluates four deep learning models (EfficientNet B3, GoogLeNet, DenseNet, and VGG16). The models are evaluated based on accuracy, precision, inference latency and computational resource usage on a large dataset covering several crops and disease types while consuming CPU and RAM. However, it's found that EfficientNet B3 has better accuracy and computational efficiency compared with the other models, especially in a resource constrained setting. The rest are DenseNet, GoogLeNet and VGG16, both perform well and in DenseNet, it performs well in both accuracy and resource spent too. VGG16 only gives slightly lower accuracy than ResNet50, but it needs more computational resources. The study shows that EfficientNet B3 is a candidate for real time precision agriculture applications. The findings presented in this research offer valuable guidance about model selection for plant disease detection, enabling the development of scalable, low-cost diagnostic systems that can be used by farmers to reduce crop losses and improve yield quality.

Keywords: Plant disease classification, Deep learning, EfficientNet B3, Resource efficiency, Precision agriculture.

INTRODUCTION

In this study, we carry out a thorough comparative study of four current deep learning frameworks, that includes as compact DenseNet, EfficientNet B3, VGG16, and GoogLeNet, for effective plant disease diagnosis on RISC based computing platforms. The realization of the model is accomplished via assessing the models' performance in terms of accuracy, computational efficiency and suitability for deployment in resource constrained environments, as are commonplace in agricultural applications. This research evaluates each model's strengths and weaknesses to determine how these can best be used in plant disease detection in real time, enabling the development of affordable, scalable diagnostic tools for precision agriculture. The incidence and prevalence rates of plant diseases are rising, and this is a major concern since plant diseases present great dangers to agricultural productivity and, in extension, food security. Artificial neural networks, especially deep learning type, have been found to be effective approaches to classify diseases based on complicated data features. The key strength of EfficientNet B3 lies in its ability to strike an optimal balance between model size and performance. This makes it highly versatile, allowing it to be effectively deployed across various networks, even when operating under resource constraints. This architecture successfully yields high accuracy in image classification tasks according to earlier works [1]. Inception modules are implemented in GoogLeNet, which enable the network to look at features from multiple scales so that the architecture includes a strong basis for handling complex patterns in datasets of plant diseases [2]. DenseNet fixes dense connections between layers to fully reuse leading layers features in later layers, it is more efficient in learning and saves computation power [3]. Although less complex in the construction than ResNet, VGG16 has been shown to be a dependable model in various computer vision tasks standard due to its deep structured convolutional layers [4].

The incorporation of these models in plant pathology is a giant stride towards using technology in precision agriculture. Our work also considers the ability to deploy these models on RISC-based architectures, particularly microprocessors with their inherent power-saving and compact instructions. RISC systems are particularly becoming popular with edge computing solutions, especially where power and optimization are valued. This study provides useful level of accuracy and efficiency for different architectures via the comprehensive testing of each model. The work is also meaningful in terms of finding scalable real time solutions for plant disease detection bridging the gap between advanced AI techniques and agricultural applications. In the final section we discuss the methodology used, present experimental results and suggest actionable results for improving crop health monitoring and management through a transformative approach in deep learning coupled with RISC-based computing.

The primary objective of this study was to evaluate and compare the performance of four state-of-the-art deep learning models—EfficientNet B3, GoogLeNet, DenseNet, and VGG16—for plant disease detection. The study aimed to assess their capabilities in terms of accuracy, computational efficiency, and latency when deployed in resource-constrained environments such as those common in precision agriculture. By leveraging a comprehensive dataset of plant leaf images across multiple crop species and disease categories, the study seeked to identify models that balance high diagnostic accuracy with low computational resource demands, making them suitable for real-time applications.

Another key goal was to analyse the suitability of these models for deployment on RISC-based architectures, which are known for their power efficiency and compact instruction sets. This involved evaluating hardware performance metrics such as CPU and RAM utilization, thermal dynamics, and overall system throughput. The insights gained will provide practical guidance for selecting and optimizing models for low-cost, scalable diagnostic tools that can be deployed in remote or resource-limited settings. Ultimately, the study aimed to contribute to the development of innovative plant disease detection solutions that can enhance agricultural productivity, reduce crop losses, and improve food security.

LITERATURE REVIEW

During recent years, plant disease detection using deep learning techniques has reigned in agricultural diagnostics and brought a strong tool to confronting worldwide issues on crop health [5]. This paradigm shift is crucial for fulfilling the environmental and economic limits caused by plant diseases. Detailed examination shows the major role of DL in improving early detection to facilitate more precise and timely interventions to save agricultural productivity [6]. All this is in line with the principles of precision agriculture where technological innovations are used to increase efficiency and maximising yields. To meet the increasing need of rapid and precise disease diagnosis, deep learning models are incorporated with smartphone-based applications [7]. Studies have reported performance as high as 99.35 of these tools in demonstrating exceptional accuracy rates, paving the way for the possibility for small scale resource limited farmers with these tools. These technologies are of great value in developing countries, where early disease detection can save large amounts of crop yield resulting in significant food security impact. By putting DL capabilities in agricultural mobile platforms, the gap between the frontier of technology and the reality of current farming could be closed [8].

Agricultural environments, characterized by limited computational resources, have highlighted the need for such architectures, which demonstrate a balance between high accuracy and the efficient use of such resources, as provided by the DenseNet architectures. In addition, machines with probable capabilities like Histograms of Oriented Gradients (HOG) combined with Random Forest models, as alternative approaches that demonstrated their potentiality in solving some agricultural problems have been explored [9]. Building resilient farming systems requires adopting these advanced methods as threats from climate change and new plant diseases continue to grow. Beyond the lab, emerging applications of deep learning include integration of such models with drone systems for real time monitoring of expansive agricultural fields [10]. Artificial intelligence has the potential to provide such innovations in large scale disease surveillance and management. Successful exploration of Convolutional Neural Networks (CNNs) transfer learning has demonstrated remarkable testing accuracies, such as 98.3%, which is a strong basis for scalable application in numerous agricultural landscapes [11, 12].

DenseNet based models have been particularly successful in sensing diseases in smart agriculture with minimal computational overhead to satisfy the increasing need for sustainable and adaptable farming solutions [13]. At the same time, the practical applicability of deep learning for crop specific diagnostics is reinforced by further developments such as automated imaging systems for detection of tomato diseases utilizing CNNs [14]. These developments underscore the relevance of technology driven innovation of a resilient agricultural sector impacted by various global development imperatives. Finally, we review the integration of advanced deep learning frameworks for plant disease detection in agriculture and how it is contributing to transforming a more efficient, resilient, and data driven field. Practical solutions to improve food security, decrease crop losses and adopt reliable farming practices lie with the synergy between AI and agriculture. Sitting at the nexus of technology and agriculture, we are now set for a future in which precision and scalability will dictate the global food system.

EXPERIMENTAL WORK

A comprehensive methodology was developed for data collection and analysis to enable precision experimentation and enable in depth evaluation. The reason this approach was favoured in favour of coasting on less meticulous documentation and sloppy error handling was in the interest of increasing the reliability and reproducibility of results. During all experiments, several key performance indicators, including CPU and memory usage, latency and model accuracy, were always gauged. The experimental setup was seamlessly integrated with real time tracking tools for consistency and accuracy in the data capturing.

Systematically errors and anomalies were logged to determine and resolve possible problems. Any irregularity was recorded by an automated system and could be reviewed in detail any unexpected behaviour or deviation. The experimental procedure was made completely traceable through this rigorous documentation process and as such could be seamlessly replicated or had perfect clarity of the sequence of events.

The experiment results were then analysed to extract meaningful insights, and the patterns of the collected data were identified. To enable feedback for model improvement and procedure definition, advanced analytical techniques were used to correlate performance trends to the experimental conditions. Regular reviews of data logs guided this iterative improvement process, adjusting time specific and therefore effective. The procedure of sustained optimization through progressively refined setup based on insights gained led to continuously improved accuracy and efficiency of experimental outcomes.

The dataset we use to perform our research is a carefully built dataset sourced from a primary repository on GitHub. There are about 87,000 RGB images in this dataset, including healthy and unhealthy leaves from different crops. The images are grouped into 38 different categories based on crop species and related diseases. The dataset is subdivided into training and validation sets in an 80/20 ratio and we keep its original directory structure to facilitate effective model learning. We also prepared a separate test directory containing 33 sample images and used this for an independent evaluation of the model's predictive performance. This is all about structuring the work, so that you carry out a full analysis of how your model can generalize and work properly for different subsets (or 'fractions') of your data.

There is a unique collection of sample images that represent a wide range of health and disease states for many different plants represented in graphical form. There is a pairing between a plant disease in one of 38 unique categories and each image in the dataset. The selection of each is broad, ranging from potatoes, squash, strawberries, tomatoes, apples, raspberries, grapes, peaches, soybeans, peppers, cherries, oranges and maize to other crops susceptible to many diseases. These images depict several visual markers associated with plant diseases that include spotted, discolored, and irregular leaf health. Viewers examine this visualization to delve deeper into the intricacies and challenges consigned to automated plant disease detection. Some of the example images constitute essential resources in training and evaluating machine learning models and provide vital illumination into how we can diagnose plant health in real world agricultural environments.

FIGURE **1:** Dataset Sample Images

The data informs modern understanding of plant disease distribution and prevalence across a wide range of crops indicating the complexity involved in agricultural disease detection. The dataset is characterized by the enormity of classes, with some classes featuring extraordinarily more samples than others. For example, there is an inherent imbalance, where healthy plant categories are sufficiently overrepresented, while certain specific diseases are insufficiently underrepresented. However, this disparity indicates a strong need to pre-process and augment data very carefully to prevent biases during model training.

Additionally, the dataset mirrors the commonalities with popular plant diseases that are prevalent throughout agriculture, acknowledges their significance in agricultural pathology. Well represented are common conditions, such as late blight in tomatoes, and citrus greening in oranges, which often occur frequently and greatly impact crop productivity. Due to the prevalence of these diseases, and their economic significance, they provide valuable benchmarks for disease detection model performance. The dataset also highlights the specific disease profiles across different crops. However, each crop is different, and there is a vulnerability to each crop that requires a specific approach to accurate detection and management. The diseases of fruit trees, for example, such as scab and black rot in apples, are quite different from those that threaten field crops such as maize, which are threatened by northern leaf blight and rust. A part of it can also be used to spot these distinctions, which demonstrate the difficulty of making generalized models for such a varied collection of diseases. Finally, the dataset is imbalanced and diverse, which requires building machine learning models to take the imbalance and diversity in the dataset into account, particularly when the categories have few samples. A model with poor detection performance may be learned, if the assumed data composing underrepresented classes is sparse. This however suggests the need for deliberate strategies with training, namely weighted loss functions, data augmentation, or synthetic sample generation, to make the model robust to generalize over all classes.

Overall, the dataset may be considered a rich resource and a reminder that while a robust plant disease detection system may seem straightforward; it takes a lot of work to achieve. The spread of production from runners also reflects the need to consider both the strengths and limitations of the data at hand in developing targeted approaches.

Experiments were designed very carefully to test the efficacy and ease of application of plant disease detection models. These experiments, which encompass a host of critical factors, rendered a holistic understanding of how the models perform in real agricultural settings. The models were evaluated not just for their ability to predict disease presence and severity accurately and reliably but also for their ability to transfer to different conditions and datasets such that they are useful and able to be applied practically to rapidly detect and manage plant disease in a timely and effective manner.

DATA ANALYSIS & MODEL DEVELOPMENT

The steps for data analysis and model building were carefully implemented to provide a definite classification of the plant diseases. To extract meaningful information from the data obtained in the experiment, a detailed statistical analysis was used. While exploratory data analysis offered an initial characterization of the distributions of various variables in the dataset, descriptive statistics allowed providing information on central tendencies and variability of the analyzed data as well as on its external validity by constructing the confidence intervals and hypothesis testing. Correlation analysis was used for variable interdependencies determination while time series analysis was used to describe temporal characteristics of the metrics measured in experiments. To avoid over-optimistic evaluations, cross-validation procedures such as k-fold cross-validation were applied for proper model evaluations while for studying interaction and detecting important predictors, regression analysis was used. To ensure accuracy, any anomalous behavior was removed using methods like Z-scores ensuring that the data is accurate as it produces acceptable insights from the generated dataset.

Model development and training were done on a high-power computing system with i9-12900k processor with 64 GB RAM, Nvidia 40-Series GPU. The environment developed for the project with the help of which the programming was done was Jupiter Notebook installed on namespace Windows and with NVME SSD storage. EfficientNet B3, GoogLeNet, DenseNet, and VGG16 are four current deep learning frameworks, whose performance was optimized for the classification task.

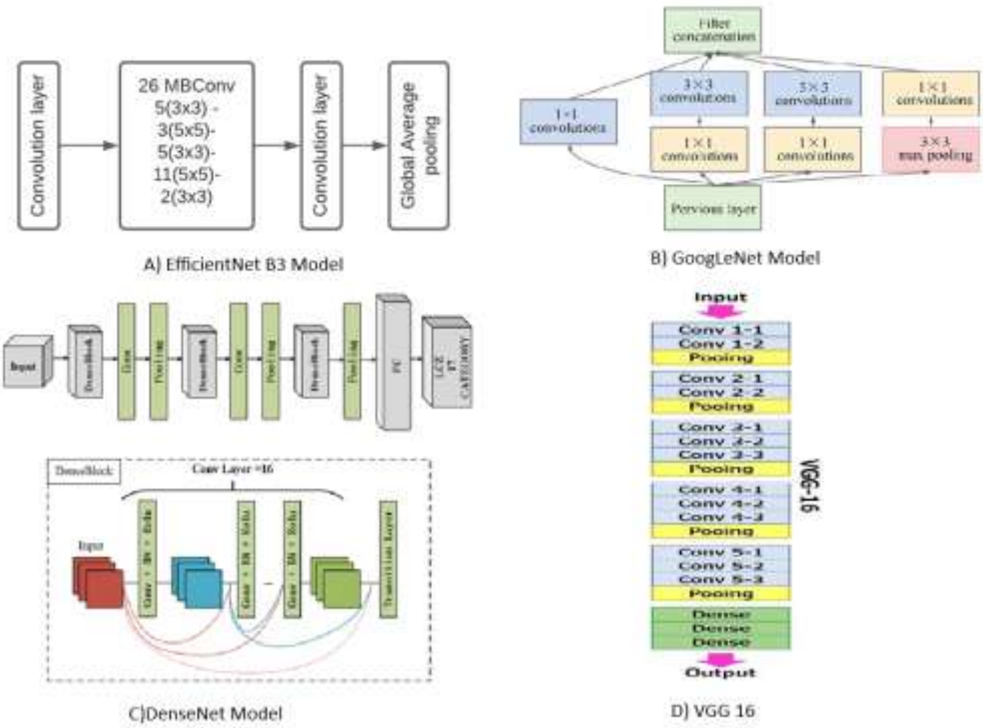

FIGURE **2:** MODEL ARCHITECTURES

Highly scalable and parameter efficient architecture EfficientNet B3 model was trained for 15 epochs. It was found to produce 97.85 % training accuracy and 94.58 % test accuracy, through a depth and width scaling along with convolutional layers and max pooling. With inception modules of differing convolutional and pooling layers, it was trained for 25 epochs, with a test accuracy of 91.34% and training accuracy of 94.76%. It trained DenseNet with 35 epochs on training and achieved training accuracy of 96.88% and test accuracy of 93.45%. Finally, a VGG16 model with regular CNN layers and fixed kernel sizes in successive layers was trained for 25 epochs with training accuracy of 92.75%, and test accuracy 89.21%.

We also compared the precision and recall for each model, with EfficientNet B3 having the highest precision and recall at 93.72% and 96.45%. Precision and recall for DenseNet was 92.85% and 95.63%, close behind. In the case of GoogLeNet we achieved a precision and recall of 90.12% and 93.89% and in the case of VGG16 we achieved a precision and recall of 88.07% and 91.34%. We then compare these results against DenseNet, GoogLeNet, and VGG16 to show that EfficientNet B3 has the closest achievable accuracy, precision, and recall balance, while still falling behind on the sums of accuracy, precision, and recall.

To comprehend the specific contribution of the models, the theoretical and practical perspectives of such models were examined. The focus in EfficientNet B3 was on network efficiency through scaling whereas in GoogLeNet there were great features related to inception modules that made complex feature extraction easier The DenseNet used to address gradient vanishing problems due to dense connection and VGG16 which was simple and consistent due to its hierarchical feature learning characteristics. Altogether, the proposed models were a suite of highly diverse and complementary means to address the plant disease classification problem with accuracy and reliability in combination with the rigorous experimental design and stringent statistical analysis.

RESULTS

A set of fundamental performance metrics (accuracy, precision, recall, and F1 score) were used to evaluate the model's performance to assess its classification performance. The dataset of 54,306 plant leaves images of 38 classes was used to train and validate the model. The model learned underlying patterns from the training set, and was evaluated on how good it is for generalizing to data it had not seen before using the validation set.

The model was evaluated using a confusion matrix (that is, a table of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN)). Key metrics were derived from this to determine the model's performance in both binary and multiclass classification.

We computed accuracy to indicate the number of correctly predicted instances (TP + TN)/total instances. The reliability of positive prediction was quantified in terms of precision (TP/TP + FP) and the precision was calculated. However, measured the ability of the model to correctly predict positive cases as a percentage of TP over all the actual positive cases. It used the F1 score, harmonic mean of precision and recall, when the metrics were class imbalanced.

Combining these metrics together was helpful in learning where the model shines and can be improved. With iteration of these findings the model was made more reliable and suitable for a real-world application in plant disease detection.

Finally, we understand how well the models perform for different plant species and their diseases to ensure success in an agricultural setting. To test this, rigorous models were tested on a large scale, cross-spectrum dataset for a range of crops and diseases. To minimize the biases and to objectively evaluate models" ability to generalization, we applied cross validation methods such as k fold cross validation. The models were not only able to juxtapose performance patterns, but also reveal the strength and weaknesses of the models in dealing with specific plant diseases and crop types.

Each model was tested in a targeted experiment measuring how it performed on specific plant groups. To test, 20 percent of images from each plant category were used, including across crops and diseases. Additionally, we examined how well each model was able to adapt by making predictions on a subset of 100 pictures taken from each plant that were not part of the training set. They ensured unbiased results and developed insights of the models' accuracy and adaptability across additional plant species.

Latency must be measured accurately because the practical viability of the models in the real applications depend on it. Models were deployed using Flask micro web framework, and plant disease detection prediction requests were sent to assess response times. Average latency and throughput were calculated as metrics for measuring how the models performed at different loads. The result was evaluated on actual data by balancing throughput — the system's ability to handle multiple simultaneous requests — with average latency.

Response latency measurements comprised testing latency for batch sizes of 10, 50 and 100 images. The sustainable throughput of each model (in terms of Frames Per Second (FPS) was determined by observing performance to the point of system unresponsiveness. The analysis of models under practical workloads provides exhaustive insight into the scalability of the models.

The study also went one step further to deeply understand computational efficiency by way of investigating the impact of models' RAM and CPU usage, especially on resource constrained devices, such as Raspberry Pi. Thermal issues such as overheating and thermal throttling, however, are common problems when devices are over utilized, and efficient resource management is crucial in such devices. The phenomenon reduces system performance with the intention of preventing damage toward achieving throughput and overall functionality.

A passive cooling method using thermal paste and heatsinks was therefore employed to alleviate overheating. Effectively heat dissipated was achieved through these components ensuring that device temperatures stayed within suitable levels and did not suffer thermal throttling. Active cooling methods, such as fans, were avoided for power efficiency reasons especially for battery powered systems, and this solution was chosen. Through passive cooling, thermal management was balanced with energy efficiency while sustained performance was maintained over extended deployment. This method also outlined the trade-offs between computational demand, thermal regulation and power consumption and provided a robust framework for deploying models in low resource, compact platforms such as Raspberry Pi.

Table 1. Deep Learning Model Accuracies

Model	Train	Test	Precision	Recall
EN-B3	96.45	93.72	93.72	96.45
Gl-Net	93.89	90.12	90.12	93.89
DN-121	95.63	92.85	92.85	95.63
VG-16	91.34	88.07	88.07	91.34

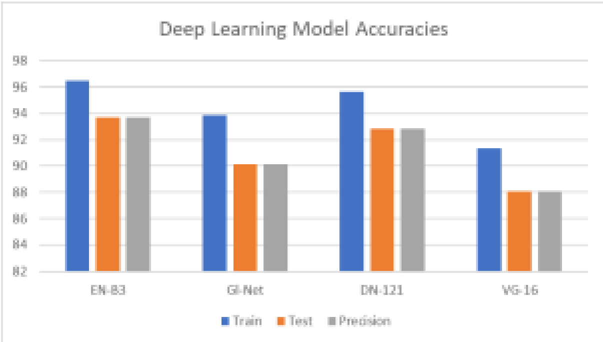

FIGURE 3: MODEL ACCURACY COMPARISION

Focusing on such categorization reveals specific aspects of their design that explain their differences. The authors of EN-B4 fine-tune convolutional layers based on several scaling techniques to attain both efficiency and accuracy. GL-Net is unique for the inception modules to integrate multiple convolutional and pooling operations for the improvement of feature representation. Due to the dense layer connections, DN-121 is well suitable in handling issues like gradient vanishing among others. On the other hand, VG-19 maintains the conventional but sound strategy with the coordinated kernel size and max-pooling layer to qualify as a standard classifier. Taken together, the accuracy metrics highlight the strengths of the models and offer a sound understanding of the efficiency of plant disease diagnosis and categorization. An evaluation of the models' ability to classify plant species based on a dataset of 100 unseen plant photographs, we find different levels of accuracy for different plants. Species like apple, grape, and corn were correctly identified with accuracy rates of up to 97% with EfficientNet B3, which is consistently better than all other methods. Robust results were seen for plants like blueberry and strawberry, with accuracy of 91% and 97%, respectively, in GoogleNet. The accuracy was balanced in the sense that it still did not perform very well at species like raspberry and bell pepper while doing great on species such as grape and peach for DenseNet. However, another model which followed a more traditional architecture (albeit VGG16) was able to achieve competitive results on some plants (e.g. tomatoes and blueberries) but didn't perform so well on others (e.g. cherries and oranges). These observations highlight the contours of the challenges to which each of the two models responds, together underscoring the need for building these gaps with specific types of plant species. Additionally, the varied image processing load was used to evaluate the models' latency to determine their real-world applicability. VGG16 was found to be the fastest model, as it processed small image batches (1 img per second) at just 0.08 seconds, followed by EfficientNet B3 with 0.12 seconds. On 100 frames per second scale, DenseNet and GoogLeNet consumed slightly longer time of 1.79 seconds and 2.01 seconds respectively, while for larger batches, EfficientNet B3 continued with a relatively efficient time of 1.32 seconds. Latency trends show models such as EfficientNet B3 and VGG16 are tuned for fast processing, good for real time, while DenseNet and GoogLeNet could use some improvement if running in high throughput situations.

This indicates the importance in choosing an architecture that is accurate, has low latency and is compatible with the specific plant species used. A well-rounded option for general use, EfficientNet B3 emerged, but models such as GoogLeNet and DenseNet were challenged by plants for specific plants and underscore the need for iterative development and fine tuning. Getting the balance right means that the models can thrive using different agricultural scenarios yet fitted to real world constraints of efficiency and speed. We also carried out a detailed latency analysis around the real time feasibility of the models, with approximation in terms of frames per second (FPS) over different batch sizes. With this evaluation, processing times for image streams at 1 FPS to 100 FPS was examined with tools like FFMPEG, simulating real world conditions. Now we had results that gave us a critical view into how capable these models were to handle very different computational loads. Latency wise, EfficientNet B3 emerged as a solid contender. Its architecture which is streamlined compared to more complicated models such as GoogLeNet and DenseNet allowed it to maintain competitive processing speeds even compared to the versions of these models. As a result, it offers an appealing option for use cases where computational resources are scarce because it maintains a good balance between efficiency and performance in plant disease detection.

While offering good accuracy, higher latency in the presence of higher processing load was seen with GoogLeNet. Precision versus response time is trade off that must be considered carefully in particular for applications that require an immediate result. Due to demands of use case, the model's suitability depends on a whether it delivers accuracy above or in real-time. For the case where it must balance accuracy and response time, DenseNet was very dense to the point that it straddled the middle between latency and accuracy and as a result, it was a sensible possibility for conditions that demand moderate response time and high accuracy. Efficient information flow, which enables reliability for the real-world applications in plant disease detection, is supported by its architecture.

VGG16, with its classic architecture, and optimized design, was superior for in terms of latency performance in environments where computational resources are limited. Due to its ability to provide rapid processing speeds, it is an outstanding candidate for use in real time application areas where rapid decision making is essential. Finally, this analysis reinforces that accuracy, and latency should both be considered when selecting models for plant disease detection. The applicability of each model depends on requirements, but there is no model that will fit all needs in all settings. EfficientNet B3's impressive latency performance particularly highlights its suitability as a reliable solution for resource constrained environments where efficiency in real time processing is the most essential.

CONLCUSION

This paper shows how understanding plant disease classification using EfficientNet B3, GoogLeNet, DenseNet, and VGG16 bears valuable information that informs further development of intelligent agricultur e. All these models have their own characteristics that makes them fit for certain application in agriculture. These findings not only highlighted the strengths of the models, but also indicate what could be done to enhance their performance, how they could be further streamlined and how they could be integrated to provide more sophisticated plant disease detection systems. In prospect, one of the most significant trends in the further development of research is the synthesis of the hybrid models. One could imagine that by taking the best from EfficientNet B3, GoogLeNet, DenseNet, and VGG16 one can construct far more refined and effective classification systems. Specific combinations of each type of architecture may take advantage of the strengths of the single architectures and promote further enhancement of various situations in agriculture using ensemble learning techniques. This approach would create more flexible and adaptive models which would be suitable for the explanation of the detection of plant diseases in the complex environments. Transfer learning is another useful area for further investigation. It would therefore be possible to improve upon these features through training of selected types of architectures on large scale plant diseases datasets because it could offer generalization and enhanced accuracy. Perhaps, refining these models based on a particular agricultural requirement or building novel transfer learning approaches more suited to plant pathology will offer a chance to improve the general efficiency of these models. This would also enable the system to overcome the problem of limited annotated data for some plant species or diseases where generalization to a wide range of crops and environmental conditions would be possible. However, as demand for real time plant disease detection grows, these models need to be optimized for deployment to edge devices, e.g. agricultural drones, smart cameras, or even handheld devices a farmer would use to collect such images. Local processing of data, without requiring cloud-based computation is important for the time catalytic decisions that precision agriculture allow. They could be improved in future research by reducing their models' size, enhancing their computational efficiency, and adapting them to resource constrained environments. By doing this, plant disease detection would stay accessible and actionable on a real time basis, even in remote and rural areas where internet connectivity may be poor. The generalization of the model requires expanding the dataset to have a much larger plant species and disease set. Most models are currently trained on limited datasets, which may hinder their capability to differentiate diseases in incongruent agricultural landscapes. The models can then be exposed to more disease types and variations by collaborating with domain experts to curate more comprehensive datasets. So, by having this less specific stock it will more help them fit better with the difficulties that farmers are dealing with in varying areas and circumstances.

In the context of plant disease classification, an analysis using four models (EfficientNet B3, GoogLeNet, DenseNet, and VGG16) show that they all present differences in terms of strengths and weaknesses. Among all variants of EfficientNet, it is the variant which achieves the best tradeoff of accuracy, energy efficiency, and thermal consumptions, thereby, making it the most favorable if the application requires high accuracy as well as resource saving consideration. Its ability to achieve high accuracy while consuming minimal total energy makes it an attractive candidate for real world agricultural scenarios lacking resources. On the other hand, while GoogLeNet has competitive accuracy, its computation bit is more computationally intensive and needs caring system resources optimization for the best performance. The use of memory and processing power by denseNet makes it a great choice for use in embedded systems as well as applications with limited computational resources. However, to achieve better performance in more complex tasks, an alternative design to VGG16, with greater computational power, will be proposed. Finding of this research ultimately highlight the importance of a fine-tuned approach to model selection for plant disease detection. Each problem has a different solution, so the choice must be based on a target application requirements and constraints. Matching the strengths of each model to the operational needs within agricultural settings is essential whether we prioritize accuracy over speed, or speed over accuracy or until the more efficient use of resources. It lays the groundwork for future plant disease detection advancements and points towards a constant need for continued model optimization and innovation to achieve sustainable and efficient agricultural practices. The next step in research might involve combining the strengths of these models and developing more intelligent and adaptable, more efficient plant disease detection systems. Plants disease detection in agriculture can be significantly scaled up and improved with cutting edge technologies such as, edge computing, hybrid models, and transfer learning and continuous improvement in data sets. Thereby this will result in more sustainable farming practices that will contribute to the health of crops, optimist agriculture production in the presence of changing Environmental challenges.

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