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COMPARATIVE ANALYSIS OF MACHINE LEARNING METHODS FOR RAPID DETECTION OF VEGETABLE DISEASE USING COMPUTER VISION

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Abstract. The timely identification of vegetable diseases is critical for food security across the globe and minimizing agricultural losses. This study compares the performances of four deep learning models – CNN, ResNet50, EfficientNetB0, and MobileNetV2 – by detecting diseases on potatoes, tomatoes, and carrots using computer vision. To determine their effectiveness, these models were trained and tested on a customized dataset and assessed on accuracy and inference time. The maximum accuracy was achieved by the CNN model, according to results. MobileNetV2 is superb; when considering both performance and extreme speed, it stands out for real-time applications. This study exemplifies how lightweight deep learning models can allow for efficient vegetable crop disease detection.



Keywords: machine learning in agriculture, convolutional neural networks, vegetable diseases and computer vision

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КОМПЬЮТЕРЛІК КӨРУ ТЕХНОЛОГИЯСЫН ПАЙДАЛАНА ОТЫРЫП, КӨКӨНІС ДАҚЫЛДАРЫНЫҢ АУРУЛАРЫН ЖЕДЕЛ АНЫҚТАУҒА АРНАЛҒАН МАШИНАЛЫҚ ОҚЫТУ ӘДІСТЕРІН САЛЫСТЫРМАЛЫ ТАЛДАУ

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Аннотация. Көкөніс дақылдарының ауруларын уақтылы анықтау жаһандық азық-түлік қауіпсіздігін қамтамасыз ету және ауыл шаруашылығындағы шығындарды азайту үшін аса маңызды. Бұл зерттеуде компьютерлік көру технологиясын

пайдалана отырып, картоп, қызанақ және сәбіз ауруларын анықтауға арналған төрт терең оқыту моделінің — CNN, ResNet50, EfficientNetB0 және MobileNetV2 — тиімділігі салыстырмалы түрде бағаланды. Олардың тиімділігін анықтау мақсатында аталған модельдер арнайы әзірленген деректер жиынтығында оқытылып, тестіленді және жіктеу дәлдігі мен инференс уақыты көрсеткіштері бойынша бағаланды. Зерттеу нәтижелеріне сәйкес, ең жоғары дәлдік көрсеткішіне CNN моделі қол жеткізді. MobileNetV2 моделі өнімділік пен жоғары өңдеу жылдамдығын қатар ескерген жағдайда жоғары тиімділік көрсетті, бұл оны нақты уақыт режиміндегі қолданбалар үшін перспективалы модель ретінде сипаттайды. Зерттеу нәтижелері жеңілдетілген терең оқыту модельдерінің көкөніс дақылдарының ауруларын тиімді анықтауға мүмкіндік беретінін көрсетеді.

Түйінді сөздер: ауыл шаруашылығындағы машиналық оқыту, конволюциялық нейрондық желілер, көкөніс дақылдарының аурулары, компьютерлік көру

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Мүдделер қақтығысы: Авторлар осы мақалада мүдделер қақтығысы жоқ деп мәлімдейді.

СРАВНИТЕЛЬНЫЙ АНАЛИЗ МЕТОДОВ МАШИННОГО ОБУЧЕНИЯ ДЛЯ БЫСТРОГО ОБНАРУЖЕНИЯ ЗАБОЛЕВАНИЙ ОВОЩНЫХ КУЛЬТУР С ИСПОЛЬЗОВАНИЕМ КОМПЬЮТЕРНОГО ЗРЕНИЯ

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Аннотация. Своевременное выявление заболеваний овощных культур имеет важное значение для обеспечения глобальной продовольственной безопасности и минимизации сельскохозяйственных потерь. В настоящем исследовании проведено сравнительное оценивание эффективности четырех моделей глубокого обучения — CNN, ResNet50, EfficientNetB0 и MobileNetV2 — для выявления заболеваний картофеля, томатов и моркови с использованием технологий компьютерного зрения. Для определения эффективности данных моделей они были обучены и протестированы на специально сформированном наборе данных, после чего оценивались по показателям точности классификации и времени инференса. Согласно полученным результатам, наибольшую точность продемонстрировала модель CNN. Модель MobileNetV2 показала высокую эффективность при одновременном учете производительности и высокой скорости обработки, что делает ее перспективной для применения в системах реального времени. Результаты исследования демонстрируют, что облегченные модели глубокого обучения могут обеспечить эффективное выявление заболеваний овощных культур.

Ключевые слова: машинное обучение в сельском хозяйстве, сверточные нейронные сети, заболевания овощных культур, компьютерное зрение

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Introduction.

In vegetable crops, early detection followed by accurate diagnosis of plant diseases is very crucial to maintaining agricultural productivity and food security. However, traditional diagnostic methods—mostly visual inspection, microscopy, and biochemical analysis—are usually very slow, tedious, and more importantly, susceptible to human error. These shortcomings are considerably amplified when separating diseases with closely related symptoms or detecting the onset of infection. Delay in interventions would certainly lead to massive spread of the diseases and considerable crop losses. In view of the above

considerations, machine-learning (ML) and computer-vision (CV) advancements offer some of the most powerful avenues for automating disease detection (Krizhevsky et al., 2017).

The recent study found out that CNNs were able to diagnose various types of plant diseases with the highest accuracy of 99.35 percent (Mohanty et al., 2016). The techniques were therefore quite fast and reliable compared to the traditional methods since they rely on symptoms that are visible to the human eye. The resolution images are then captured from healthy and diseased plants using IoT-enabled sensors in agricultural fields. High resolution is very important for correct detection, so different pre-processing techniques such as noise removal, distortion corrections, and color space conversions are applied to enhance these images for further consideration (Sladojevic et al., 2016). Cost-cutting, labor-saving, and prompt results are some of the ways in which these systems are thus improving the overall crop health management through an automated disease diagnosis (Loey et al., 2020). In addition, the application of IoT-based sensors and imaging technologies facilitates real-time data acquisition and disease monitoring in agriculture (Mohanty et al., 2016). This paper emphasizes the performance evaluation of four major deep learning models, that is, CNN, ResNet50, EfficientNetB0, and MobileNetV2, for vegetable disease recognition, specifically potatoes, tomatoes, and carrots. These models were trained and tested on a dataset of images of healthy and diseased vegetable varieties, and their performance was evaluated with respect to the main performance measures: accuracy and inference time. To identify that model which is best in terms of accuracy and computational efficiency for use in the field.

The study covers the following: network architecture, data pre-processing techniques, system evaluation, and the challenges faced during the experiment. The study further indicates possible more generalization-enhancing techniques, such as data augmentation and fine-tuning strategies. This paper provides a comprehensive comparison of the models' capabilities and examines their suitability for real-time deployment in mobile devices and embedded systems, which becomes important for actual agricultural settings. The key hypothesis working behind this study is that although certain models, for example CNN, have scored sufficient accuracy in a controlled environment, what happens outside that environment remains questionable upon testing from a database that it did not come across during real-time? With offline testing on custom datasets, this research intends to ascertain the effectiveness and practicality of these models in real-world scenarios, thereby bridging the gap between theoretical advancement and agricultural demand. The present study, unlike earlier research which was restricted to single-crop datasets, offers a cross-crop evaluation (potato, tomato, carrot) based on a common architecture-comparison framework that is intended for real-time agricultural applications. The study aims to answer the following research questions:

- Which model (CNN, ResNet50, EfficientNetB0, MobileNetV2) demonstrated the best accuracy in classifying vegetable diseases?
- What inference time did the models show when processing images, and which model was the fastest for real-time applications?

- How did image preprocessing techniques, such as data augmentation, impact the accuracy of the models?
- How do the performance and accuracy of models with more complex architectures (ResNet50) compare to lightweight models (MobileNetV2) for disease detection tasks in agriculture?

Materials and methods.

Plant disease detection via deep learning has been an active research area in recent years. Tomato and potato plant disease classification was performed by Mohanty et al. (Mohanty et al., 2016) using CNNs. Disease detection in apple leaves was conducted by Sladojevic et al. (Sladojevic et al., 2016) using the same methodology. However, most existing works address a specific crop or a limited number of diseases. Hence, this research aims to widen the horizon by testing many models on three different vegetables, thereby permitting a thorough comparison of their diagnostic abilities.

Against this background, recent deep learning breakthroughs with the rise of architectures such as Transformers and Graph Neural Networks (GNNs) should enable the integration of multimodal data, like combining images with volatile organic compound (VOC) signals, for enhanced plant health monitoring (Domingues et al., 2022). While Transformers were initially designed for natural language processing, they adopt attention mechanisms to discern important features within the sequential data, such as time-series VOC signals, making them well-suited for the integration of visual and sequential data streams (MacDougall et al., 2022). On the contrary, GNNs are adept at fitting their interconnected data points, like the relationships between different features of a plant or the temporal patterns of VOC emissions (Alomar et al., 2023). These innovations are a great leap within precision agriculture.

In studies that come just before this one, advanced models like YOLOv3 and YOLOv5 are used for real-time disease detection. For instance, YOLOv3 can effectively detect tomato diseases and pests with an accuracy of 92.39 % (Liu et al., 2020). YOLOv5 for vegetable disease detection, reported an accuracy of 93.1 %. These models become more relevant for real-time application due to their speed and efficiency (Li et al., 2022).

In addition to agriculture-specific applications, intelligent monitoring systems in other domains also demonstrate the effectiveness of integrating machine learning and real-time data processing. For example, Nurgaliyeva et al. developed an RGIS-based intelligent waste monitoring system aimed at improving environmental management in smart cities, highlighting the role of spatial analytics and automated decision-making in large-scale monitoring tasks (Nurgaliyeva et al., 2025). Similarly, another study by Nurgaliyeva et al. proposed an intelligent system for evaluating risk factors affecting public transport drivers using multimodal sensor data and machine-learning models (Nurgaliyeva et al., 2025). Although these works belong to different application areas, the methodological principles, like computer vision, real-time analysis, and adaptive model integration, are directly relevant for designing robust plant disease detection systems.

Another place where recent development has been seen is in transfer learning and feature fusion. Relying on the fusion of two models-MobileNetV2 and DenseNet201-

achieved 95.7% accuracy in citrus disease classification (Rehman et al., 2021). This is one way of applying pre-trained models to a specific task, allowing for improved performance. This mitigates the need for large datasets and lengthy training sessions. In addition, used deep learning-based segmentation techniques with 99.2 % accuracy for detecting plant leaf diseases which indicates the promise of integrating CNNs with semantic segmentation for accurate disease mapping (Shoaib et al., 2022).

The role of image preprocessing techniques, especially data augmentations, is crucial for improving the performance of models used in plant disease detection. Data augmentation artificially increases the size of the dataset by applying various transformations, such as rotations, flipping, or color alterations, to an existing image. This will enable the model to learn a more diversified set of features, thus enhancing its ability to generalize on unseen data and improving ultimate accuracy. For instance, one paper demonstrated that the use of tools like LeafGAN for generating a variety of diseased images from healthy ones can increase their model diagnostic accuracy by 7.4 % (Cap et al., 2020). This is evidence on the effectiveness of data augmentation for better performance enhancement. Yet a different study showed that the combination of different data augmentation techniques, including rotation and scaling, always gave an increase in model accuracy by about 25 % starting with even a small number of seed images (Xiao, 2022). Lastly, the study added that dataset augmentation with synthetic data generated by models like CycleGAN and pix2pix improved the accuracy of coffee leaf disease detection. This shows how augmentation is significant for handling imbalanced datasets so that some disease labels may be underrepresented (Gheorghiu et al., 2024). Overall, these studies establish that data augmentation can significantly improve model accuracy by expanding the dataset, inducing variability, and making the model learn generalized features. Thus, the real-life performance is enhanced-in plant disease detection, in particular.

In agricultural disease detection, heavier architectures like ResNet50 models are often juxtaposed against lightweight models, such as the MobileNetV2. Several deep neural networks, namely, VGG16, ResNet-50, Inception-V3, Inception-ResNet-v2, and MobileNetV2 were evaluated for weed recognition tasks. The results showed that VGG16 carried out better with small- scale datasets, while ResNet-50 proved superior among others with a larger consolidated dataset, thus hinting that complex architectures can go for increased accuracy when an ample amount of data is supplied (Hasan et al., 2021). Another study explored the performance of the three models: ResNet50, VGG16, and MobileNetV3-Small. The tested conclusions indicated that MobileNetV3-Small can provide testing data with high accuracy of 79%, which means that lightweight models can be powerful in real disease detection cases, especially in situations when resources to operate are scarce (Roseno et al., 2024).

Recent data-driven modeling research is extending its deep-learning applications apart from traditional image classification tasks, particularly in agriculture and energy systems. Assembayeva et al. (Assembayeva et al., 2019) constructed the dataset describing spatial electricity market in Kazakhstan, thereby bringing into focus the need for geographically distributed data and real-time monitoring infrastructure-both concepts

which matter as much in large-scale agricultural systems where region-specific disease detection becomes necessary. Furthermore, the approach proposed by Satan et al. (Satan et al., 2025) considers neural network regression framework for energy load forecasting integrated with feature engineering and clustering to offset climatic variability. Their achievement in enhancing prediction accuracy through identification of sensitive time windows and correlation of performance with external variables like temperature shows interesting parallels to agriculture where the spread of disease could also be contingent upon environmental parameters such as humidity and heat. This is where these studies open up possible avenues for future work in linking environment sensors and deep learning to increase real-time responsiveness of plant disease detection systems.

The above highlights that the choice between heavy and lightweight models will depend on the dataset size, constraints of computational resources, and the specific needs of the disease detection task. On the one hand, heavier models such as ResNet50 offer higher accuracy when used with large datasets; on the other hand, lightweight models such as MobileNetV2 can achieve comparable performance with less computational burden, thus suiting them for situations needing real-time job execution and deployment on resource-constrained systems.

While prior studies have shown the success of CNN-based models for disease detection in crops including tomatoes or apples, our study aims to broaden this evaluation by considering the performance in three classes of vegetables, namely potato, tomato, and carrot, using a custom multi-crop dataset; this really helps in assessing generalization in a wider context. Many studies only focus on accuracy, but real-time inference time is very important in research that is meant to find applications in agricultural scenarios. Therefore, we assess lightweight MobileNetV2 with heavyweight ResNet50 and EfficientNetB0, providing some insight into trade-offs between accuracy and applicability while thus closing an important gap in comparative performance analysis.

Additionally, the utilization of transfer learning with fine-tuning, far more applications of synthetic data augmentation (CycleGAN and LeafGAN), and investigating more recent augmentation pipelines will also be discussed.

Some models showed activity, however how they perform on datasets that are pre-collected and are not captured in real-time conditions is unknown. This paper represents an attempt to fill this gap by evaluating the applicability and limitations of the models applied against such datasets. In terms of plant diseases detection systems, the merging of deep learning, computer vision, and advanced signal processing will tremendously increase their potential, yet more studies must be conducted. Knowledge of these limitations and modifying technology to meet the demands of agriculture will then lead to further realization of its potential.

The data set for this study, «Fruit and Vegetable disease (Healthy vs Rotten)» (Subhan et al., 2024), was obtained from Kaggle and comprises clear images containing healthy and diseased potatoes, tomatoes, and carrots. comprises images of healthy and diseased potatoes, tomatoes, and carrots, with a total of 6 classes (healthy and rotten for each vegetable). The dataset includes approximately 3,000 JPEG/PNG images,

with varying resolutions (recommended to resize to 224x224 for model consistency). Preprocessing steps included pixel normalization (scaling pixel values to [0, 1]), rotation, zooming, and horizontal flipping using TensorFlow's ImageDataGenerator to enhance data variety. The dataset was split into 80 % training and 20 % validation sets to ensure robust evaluation on unseen data. Data augmentation techniques, such as rotation, flipping, and zooming, were applied to artificially expand the dataset, mitigate overfitting, and improve model generalization. To make the models robust and generalizable, several preprocessing steps were carried out:

- **Image Preprocessing.** Includes pixel normalization (scaling pixel values within [0, 1]), rotation, zooming, and horizontal flipping, and added ImageGenetrator of preprocessing functions from TensorFlow. This caused the introduction of verogeneity in training data for better generalization in the model.

- **Data Segmentation:** The corpus was segmented into training and validation data, maintaining a ratio of 80:20. Thus, the model is now verified on unseen data, turning in a better assessment of performance.

- **Data Augmentation:** By zooming, flipping, and rotating, the dataset was artificially inflated and diversified, which is the key in avoiding overfitting when data are limited.

Four deep learning architectures were selected for evaluation:

- A custom CNN was designed with three convolutional layers followed by max-pooling layers for reducing spatial dimensions, and the last two layers being dense for classification, thus making this architecture light and specific to the task of disease detection.

- ResNet50 refers to a pre-trained deep CNN having 50-layer architecture called on their residual learning framework. The model was fine-tuned by replacing the last fully connected layer with a global average pooling layer and a dense output layer for binary classification.

- EfficientNetB0 is a pre-trained model aimed at achieving maximum efficiency and accuracy. It employs a compound scaling method to uniformly scale all dimensions of depth, width, and resolution. The model was fine-tuned for binary classification by modifying the final layers.

- MobileNetV2 is another lightweight and pre-trained model suitable for mobile devices and embedded systems. It implements inverted residual blocks with linear bottlenecks to reduce computation costs. Fine-tuning for binary classification was done by modifying the last layers of the model.

The flowchart above visualizes and compares the internal structure of the four deep learning architectures used in this study: CNN, ResNet50, EfficientNetB0, and MobileNetV2.

The custom Convolutional Neural Network(blue) begins with an input layer (224×224×3) followed by three consecutive convolutional layers (Conv1, Conv2, Conv3) with increasing filter sizes (32, 64, 128) and max-pooling layers to progressively reduce spatial dimensions and extract hierarchical features. The Flatten layer converts 2D feature

maps into a 1D vector, which is fed into a dense (fully connected) layer with 128 neurons, followed by dropout to prevent overfitting. The final sigmoid output layer performs binary classification (healthy vs diseased). This simple sequential structure allows the model to learn spatial patterns efficiently while maintaining low computational cost.

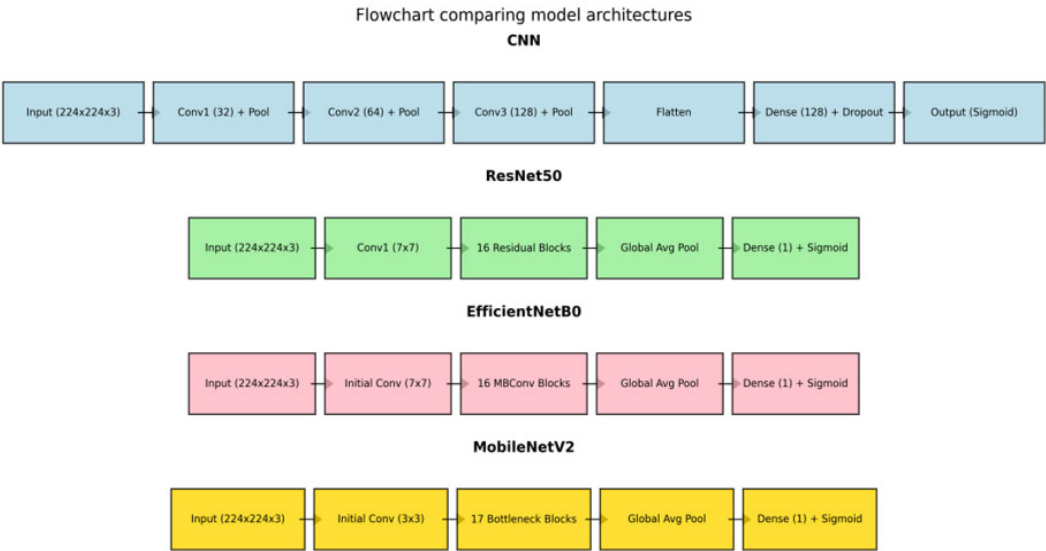


Fig. 1. Flowchart of used model architectures.

The ResNet50(green) architecture starts with a 7×7 convolutional layer, followed by 16 residual blocks that use skip connections to bypass one or more layers. These shortcuts help mitigate the vanishing-gradient problem and allow the network to learn deeper representations. A global average pooling layer replaces the traditional fully connected layers to reduce overfitting, followed by a dense sigmoid output layer for binary classification.

EfficientNetB0(pink) applies a compound scaling approach that uniformly scales depth, width, and resolution for optimal efficiency. It begins with an initial 7×7 convolution, continues with 16 MBConv (mobile inverted bottleneck) blocks that expand and compress feature maps efficiently, and ends with a global average pooling and dense sigmoid layer. This design balances accuracy and computational cost, making it highly efficient for transfer learning tasks.

The MobileNetV2(yellow) architecture also starts with an initial convolution layer (3×3), followed by 17 bottleneck blocks that use inverted residuals with linear bottlenecks, minimizing the number of parameters while preserving representational power. A global average pooling layer aggregates spatial features before the final dense sigmoid output. The lightweight structure makes MobileNetV2 ideal for deployment on mobile and embedded systems with limited resources.

Training details Adam optimizer with binary cross-entropy (1) loss was deployed for

training purposes for all models for five epochs. The batch size was 32, and the images were resized to 224x224 to retain the same size among all models being developed. ResNet50, EfficientNetB0, and MobileNetV2 were set for transfer learning, with pretrained weights from ImageNet. In this way, the model can benefit from the previously learned features, thus reducing the amount of training required on the target dataset.

Explanation for Binary Cross-Entropy (BCE):

$$BCE = \frac{-1}{N} \sum_{i=1}^N [y_i * \log(\hat{y}_i) + (1 - y_i) * \log(1 - \hat{y}_i)] \quad (1)$$

The Binary Cross-Entropy (BCE) loss function was employed to optimize the model during training. It measures the difference between the predicted probabilities and the true class labels for each sample. Lower BCE values indicate better alignment between predictions and ground truth. This loss is particularly suitable for binary classification tasks like healthy versus diseased plant detection. The Adam optimizer minimizes this loss by adaptively adjusting learning rates during training, ensuring faster and more stable convergence.

Metric of Assessment. The most significant metric used to assess the model's performance is classification accuracy (2), which expresses how many images of those presented have been classified correctly. The models' time to process a single image would be calculated, which is another important measure of computational efficiency. This parameter holds vital importance, particularly in real-time applications, as speed is equal in importance to accuracy.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (2)$$

True Positives (TP): correctly identified diseased samples.

True Negatives (TN): correctly identified healthy samples.

False Positives (FP): healthy samples incorrectly classified as diseased.

False Negatives (FN): diseased samples incorrectly classified as healthy.

Accuracy represents the overall proportion of correctly classified instances out of all predictions made. While it provides a general measure of performance, it can be misleading in cases of class imbalance, for instance, when one class (healthy samples) significantly outnumbers the other (diseased samples). In such cases, the model may achieve high accuracy simply by predicting the majority class more often.

The performance of each of the models was evaluated on the validation set, and a comparison was made among the various vegetables (potatoes, tomatoes, and carrots). For all models, the accuracies and inference times were recorded and subsequently analyzed to declare the model with the highest performance for each corresponding task.

Challenges and Mitigation. Overfitting was taken care of by using data augmentation

methods and limiting the number of training epochs. Dropout layers have been introduced in the custom CNN to curb the model's dependency on overly specific features. Class imbalance was checked for, and then techniques like oversampling and data augmentation were used to ensure that the models were not biased against the majority class.

Besides the accuracy and time for inference, the confusion matrices were computed for each of the models and for each of the vegetable categories. These matrices indicated that the false negatives were more prevalent than the false positives, especially in the case of tomato diseases, therefore posing a higher threat for infections that cannot be detected and therefore inflict greater crop losses. In furtherance to obtain a nuanced measure of the performance of our models, additional performance matrices like precision (3), recall (4), and F1-score (5) were calculated since high rates of false negatives are detrimental to agricultural applications. The F1-scores for all the vegetable types were greater than 0.85 in the CNN model, and MobileNetV2 also showed balanced values of recall and precision development. Thus, keeping in view the above, MobileNetV2 is qualified to perform on mobile. Other than that, ResNet50 and EfficientNetB0 had less recall, especially on the minority classes, which may also indicate the possibilities of overfitting on this small dataset.

Explanation of metrics:

$$\text{Precision} = \frac{TP}{TP+FP} \quad (3)$$

True Positives (TP): correctly identified diseased samples.

False Positives (FP): healthy samples incorrectly classified as diseased.

Precision quantifies the reliability of positive predictions, i.e., the proportion of samples predicted as diseased that are actually diseased. High precision indicates a low false positive rate, which is particularly important in agricultural applications to avoid unnecessary interventions for healthy crops.

$$\text{Recall} = \frac{TP}{TP+FN} \quad (4)$$

True Positives (TP): correctly identified diseased samples.

False Negatives (FN): diseased samples incorrectly classified as healthy.

Recall, also known as sensitivity, measures the model's ability to correctly identify diseased plants. A high recall value means that most of the diseased samples are successfully detected. In plant disease detection, this metric is crucial because false negatives (undetected infections) can lead to large-scale crop losses if not treated in time.

$$F1 - Score = \frac{2 * Precision * Recall}{Precision + Recall}$$

(5)

The F1-score is the harmonic mean of precision and recall. It balances the trade-off between the two metrics, offering a single measure that reflects both the accuracy of positive predictions and the completeness of disease detection. An F1-score closer to 1 indicates better model performance.

This was explored further by training the models’ performances on TensorFlow and Keras, using transfer learning for ResNet50, EfficientNetB0, and MobileNetV2, and a custom architecture for CNN.

Implementation details

- Framework: TensorFlow and Keras for model implementation, training, and evaluation.
- Hardware: A GPU-enabled system was used for training, hence no delay in computation, and it hastened the chances of training.
- Visualization: The graphs for the learning accuracy and validation curves were built to monitor the effectiveness of the model in different epochs. Confusion matrices were also generated to analyze the classification effectiveness of each model, after which Excel tables were created based on the data obtained. These tables were imported into Power BI and presented as graphs.

Data augmentation and fine-tuning strategies

- Data augmentation. A model was trained using data augmentation techniques such as rotation, flipping, zooming, and color jittering to increase variance in the training data. The main aim was to help the model generalize well to unseen data and mitigate overfitting risk. Also, data generated synthetically using CycleGAN and LeafGAN models were explored in strengthening the dataset, especially for less represented disease types.
- Fine-tuning on the pretrained models (ResNet50, EfficientNetB0, MobileNetV2) was done by freezing the initial layers and training only the final layers. These models can be fine-tuned to the specific task while retaining the general features learned from ImageNet and thus be made more suitable for the proposed tasks. Also, learning rate scheduling was used to reduce learning rate decrease at training intervals gradually. Hence, ensuring convergence stability and preventing overfitting.

Results and discussion.

The results for each vegetable and model are summarized below. The classification accuracy of the models is presented in Table 1, and the corresponding inference times are shown in Table 2.

Table 1. Accuracy comparison of models across vegetable

Model	Accuracy (Potato)	Accuracy (Carrot)	Accuracy (Tomato)
CNN	86.38 %	87.66 %	88.98 %
ResNet50	51.49 %	51.91 %	49.58 %
EfficientNetB0	51.49 %	48.09 %	49.58 %
MobileNetV2	80.00 %	80.85 %	67.80 %



Between classification of diseases in potatoes, the best-performing model was the CNN, achieving the highest accuracy of 86.38 % while also recording the fastest inference time of 0.12 seconds. Fast and effective in capturing disease-specific features, the architecture is believed to suit the image classification tasks best. In having relatively poor accuracies of 51.49 % and 51.49 % with ResNet50 and EfficientNetB0, respectively, their inference times due to potentially being overfitted and being effectively inefficient in extracting the relevant features from the images of the potatoes. MobileNetV2 achieved an accuracy of 80.00 % and inference time of 0.12 seconds, thus providing a trade-off between accuracy and speed.

Table 2. Inference time of models

Model	Time/s (Potato)	Time/s (Carrot)	Time/s (Tomato)
CNN	0.151637	0.128340	0.120292
ResNet50	0.583162	0.595224	0.487197
EfficientNetB0	0.690384	0.665401	0.173446
MobileNetV2	0.414888	0.396843	0.131842

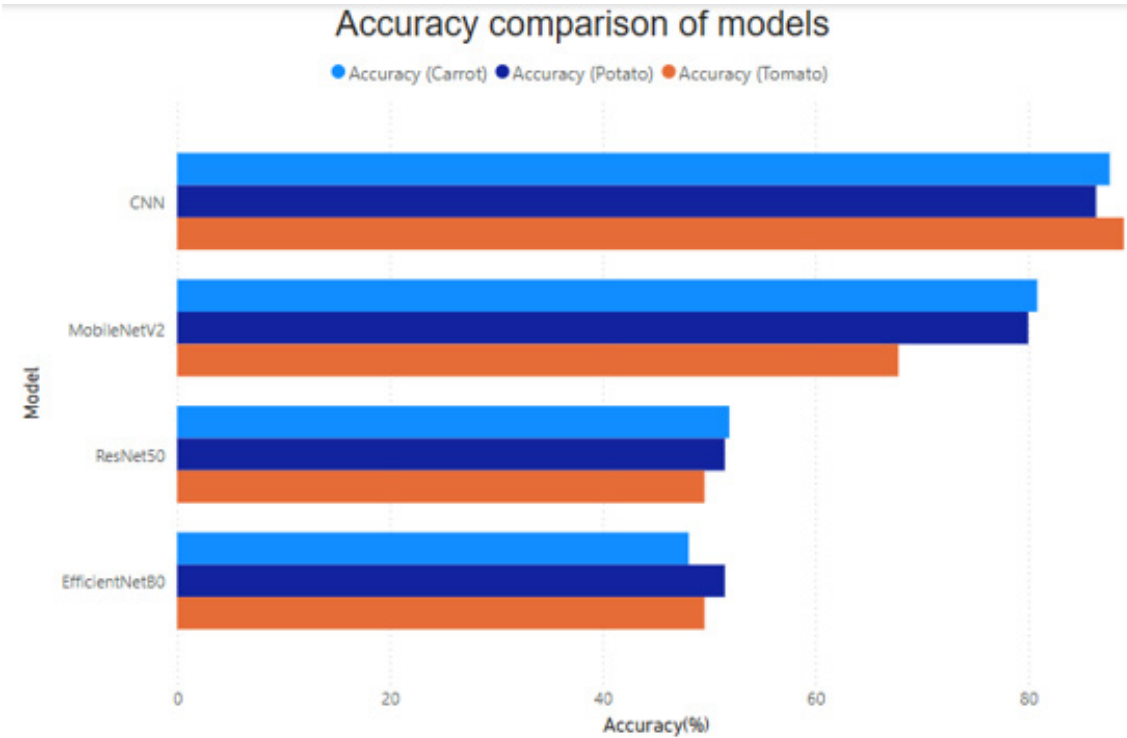


Fig. 2. Accuracy comparison of models.

For carrots, CNN scored the highest in accuracy and lowest in inference with results of 87.66 % and 0.13 seconds, respectively. Other models, such as MobileNetV2, came in close at 80.85 % accuracy and 0.40 seconds inference, making it likely a great fit for real-time applications. ResNet50 and EfficientNetB0, however, suffered low accuracies (51.91 % and 48.09 %, respectively) and low inferencing times, suggesting that some

optimization is needed for carrot disease detection for these two to perform adequately.

In tomatoes, CNN, with accuracy ratings of 88.98% and moderate inference times of 0.12 seconds, stood its ground. However, the accuracy of MobileNetV2 had dropped to 67.80 %, quite a marked decrement compared with its performance on potatoes and carrots. As for ResNet50 and EfficientNetB0, they did poorly once more, both with accuracies of 49.58 %, but EfficientNetB0 was faster, at 0.17 seconds, than ResNet50’s 0.49 seconds.

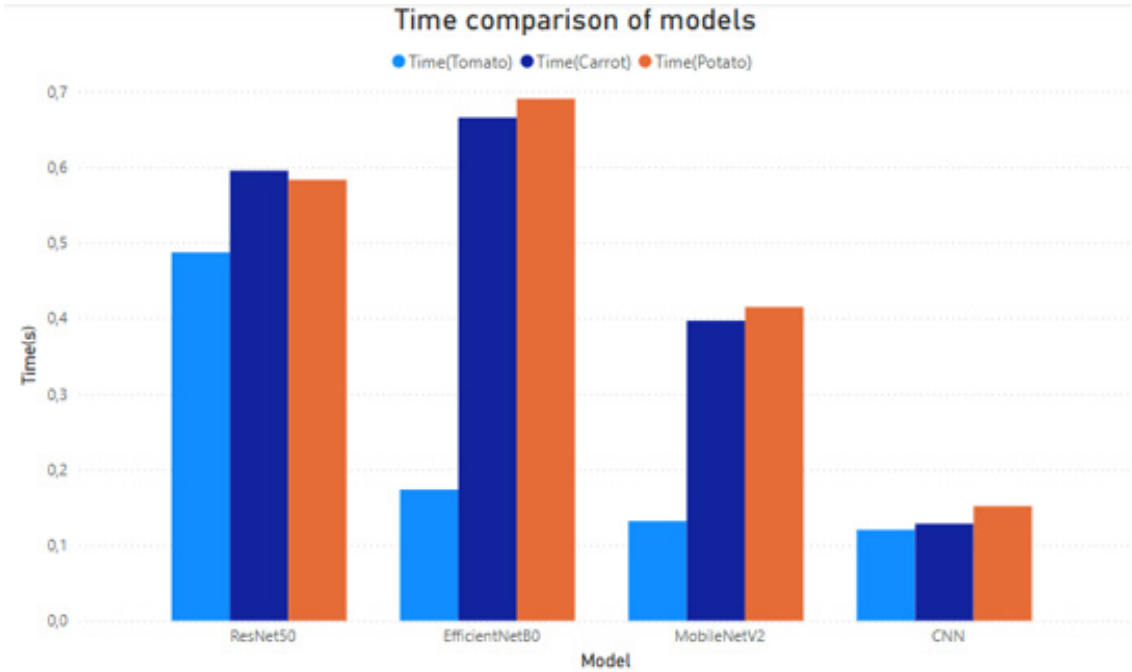


Fig. 3. Time comparison of models.

Model comparison and practical applicability:

- CNN. The CNN model has always been placed on top, both regarding accuracy and inference time, for all the three datasets under study. This places the model as a potentially ready candidate for deployment in disease-detection applications, especially in cases where temporal factors are of utmost importance, like in-field diagnosis.
- MobileNetV2. With a balanced performance, MobileNetV2 offers a good compromise between accuracy and inference time, making it especially suited for deployment on mobile/embedded platforms with limited computational resources.
- ResNet50 and EfficientNetB0. Both models consistently rated poorly in accuracy across all datasets and took equally long inference times. Perhaps there is potential for further optimization and fine-tuning; however, the present performance of these models in their current form indicates silos for real-time applications.

On one hand, there are very encouraging results from CNN and MobileNetV2; on the other hand, several challenges required for their deployment in real-world applications must CycleGAN be met. The models were trained and validated on a controlled dataset, and

therefore, their performance in various real-world conditions such as lighting, background noise, and different image qualities would vary. In addition, the low performance of deeper models such as ResNet50 may be due to scarce data or domain mismatch in transfer learning.

In addition, these models will need to be integrated into hardware-constrained environments and deployed for real-world use, such as on drones or smartphones. Although MobileNetV2 has considerable promise in this area, more optimization, such as model quantization and pruning, would be helpful. Moving forward, more field testing involving actual crop images would be done for incremental model retraining for adapting models to changing environments.

Conclusion.

The research presented four deep-learning models, namely, CNN, ResNet50, EfficientNetB0, and MobileNetV2, for the detection of vegetable diseases, using computer vision methodologies for identification in potatoes, tomatoes, and carrots. The assessment would be based on whether the algorithm is efficient in terms of accuracy and inference time so that real-time applications could be setup for the identified needs in agriculture.

Across the board of all vegetable types, the highest classification rates were manifested by CNNs; therefore, accuracy was highest in this architecture. CNN was seen as the superior architecture in this research work to detect disease patterns in the vegetable crops; 86.38-percent potato, 87.66-percent carrot, and 88.98-percent tomato. Apart from the accuracy of CNN, it was recorded that the overall inference time of each vegetable dataset was the quickest: 0.12 seconds for potatoes, 0.13 seconds for carrots, and 0.12 seconds for tomatoes. Hence, this speed, coupled with accuracy, positions CNN as a highly probable candidate for real-time applications concerning agricultural disease detection.

ResNet50 and EfficientNetB0, despite having more complex architectures, performed poorly concerning accuracy and inference time compared to MobileNetV2. ResNet50 has been reported to be accurate when using large datasets; however, this work had limited performance due to overfitting from the small dataset used. Being lightweight, MobileNetV2 provided good accuracy against inference time, making it a good candidate for deployment in resource-constrained mobile or embedded systems in agricultural applications.

CNN holds an edge over other models for vegetable disease classification, specifically for real-time applications because of its very high accuracy and quick processing time. MobileNetV2 is also a strong candidate for real-time applications, providing a very good compromise in between accuracy and computational costs. However, much more complex algorithms like ResNet50 and EfficientNetB0 must be optimized to realize their full potential in real-world scenarios, especially on smaller custom datasets. Findings here suggest lightweight models can be handy in real-time agricultural disease detection, paving the road for their field-based application concerning crop health management and reducing agricultural losses.

Future work will be to create a unique dataset from farms in Kazakhstan that will be used for domain adaptation. The mobile application for field-level disease diagnosis is

planned to incorporate the models that have been trained, with MobileNetV2 being the primary one.

The future research will be mainly directed to three distinct areas:

To begin with, the dataset will be noticeably increased through the high-quality images of vegetables collected from local farms and research centers in Kazakhstan. Such an expansion will lead to better model generalization and will also help in eliminating the bias that results from the limited diversity of the samples. Moreover, synthetic data generation will be used through the application of advanced augmentation methods such as CycleGAN and LeafGAN to balance the classes of diseases that are underrepresented.

In the second place, the proposed models will be subjected to real-world testing under different environmental conditions, such as changing light, background noise, and leaf surface being dirty. Such a test will be conducted to verify the model's strength and its ability to adapt to uncontrolled field environments.

In the third place, the models that have been developed will be integrated into the systems that are enabled by IoT for the purpose of carrying out continuous crop monitoring. Real-time disease detection and early-warning systems for precision agriculture will be supported by the fusion of visual analysis with environmental sensor data (e.g., humidity, temperature). The ultimate goal is to incorporate lightweight architectures like MobileNetV2 into mobile and drone-based platforms making it easier for them to be deployed in agricultural fields practically.

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