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Implementation of machine learning model in classification of potato leaf diseases

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Abstract

In the contemporary agricultural landscape, Machine Learning (ML) has emerged as a sophisticated paradigm for the automated detection and classification of phytopathology via leaf-based image analysis. This research evaluates and contrasts the diagnostic efficacy of four distinct computational frameworks, Random Forest, XGBoost, Support Vector Machine (SVM), and Convolutional Neural Networks (CNN), specifically for the identification of potato foliage diseases. Utilizing a curated dataset encompassing 'Early Blight,' 'Late Blight,' and 'Healthy' specimens sourced from both public repositories and empirical field data, the investigation demonstrates that all four architectures achieve superior performance metrics and robust classification accuracy. The CNN with VGG16 outperformed the Random Forest, SVM, and XGBoost models in potato leaf disease classification. While SVM achieved strong and balanced performance (0.91 accuracy), and XGBoost and Random Forest produced satisfactory results (0.85 and 0.82 accuracy, respectively), the VGG16-based CNN achieved the highest overall accuracy of 0.96 with consistently superior precision, recall, and F1-scores across all classes. These findings indicate that deep learning, particularly the VGG16 architecture, provides more robust feature representation and improved discriminative capability for image-based plant disease classification task. This finding contributes to the development of a Machine Learning-based plant disease detection system in the smart agriculture sector.

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Keywords

Accuracy, CNN, Random forest, SVM, XGBoost, Machine learning

Introduction

Potatoes (*Solanum tuberosum L.*) are one of the most important food commodities worldwide, particularly in Indonesia. Potato plants have significant economic value as a food source, industrial products, and raw materials for agriculture. However, like other crops, potatoes are susceptible to pests and diseases that can reduce production yields and the quality of the plants. Diseases such as late blight and pest infestations like aphids often result in considerable losses in potato crops. Early detection of these pests and diseases is crucial for effective agricultural management, given their impact on harvests and production costs.

With the rapid development of technology, the application of Machine Learning (ML) in agriculture has become increasingly popular as a solution for detecting and classifying plant diseases and pests. Machine Learning models can assist in analyzing potato leaf images, identifying patterns that indicate the presence of diseases or pests, and providing appropriate action recommendations. In this context, algorithms such as Random Forest, XGBoost, Support Vector Machine (SVM), and Convolutional Neural Network (CNN) have been widely used due to their ability to handle complex data and classify objects accurately.

The Random Forest framework operates as an ensemble of decision trees, where the definitive classification is reached through a majority voting consensus across all constituent learners. Previous research by [1] demonstrated the efficacy of this model in diagnosing botanical pathologies, achieving high accuracy by leveraging the textural attributes of leaf imagery. Similarly, Extreme Gradient Boosting (XGBoost) has emerged as a powerful supervised learning tool that iteratively refines model performance by optimizing loss functions through a boosting mechanism; for instance, [2] reported a 98% accuracy rate when employing XGBoost for agricultural selection tasks. In contrast, Support Vector Machines (SVM) utilize high-dimensional spatial mapping to identify an optimal separating hyperplane, a technique particularly suited for datasets with limited samples but high dimensionality. This was evidenced by [3], whose multi-SVM approach for potato disease detection using spectral data yielded a precision of 86.67%. More recently, deep learning advancements have seen CNN models achieve superior results, with [4] reporting a 95% classification accuracy in the identification of potato foliage infections.

Additionally, several other studies have also shown the success of applying Machine Learning algorithms in detecting diseases and pests in potato plants. [5] Developed a hybrid model by combining CNN and Vision Transformer (ViT) for plant disease detection, achieving high accuracy and enhancing detection, which promises advancements in plant disease management. On the other hand, [6] used a VGG16-based CNN to identify pests attacking potato plants, with results indicating that the algorithm could detect pests with up to 85% accuracy.

The application of plant disease detection in potatoes was also explored [7] in their study titled “Deep Learning and Explainable AI for Classification of Potato Leaf Diseases.” This study presents an integrated approach utilizing Explainable AI (XAI) and transfer learning within a deep learning framework. The study “ML-Based Approach to Potato Diseases Diagnosis Using Image Processing and Whale Optimization Algorithm for Feature Selection” by [8] demonstrated that the proposed method achieved high accuracy levels, with 99.04% for SVM and 96.49% for WOA. The precision for diagnosing early leaf rot, late leaf rot, and healthy leaves was 96.29%, 96.29%, and 97.44%, respectively. Research [9] evaluated five different CNN architectures: VGG16, VGG19, MobileNetV2, ResNet50, and AlexNet, to assess their classification capabilities. The findings revealed that ResNet50 performed the best, achieving an exceptional testing accuracy of 97% and specificity of 98%.

Recent research in pest and disease detection in potatoes has shown significant progress in the application of Machine Learning and Deep Learning algorithms to improve detection accuracy and efficiency. Deep learning-based approaches, especially those combining CNN and ViT, have proven to be capable of handling more complex leaf images and providing more accurate results, as seen in the studies of [10], [11], [12]. Although previous research [13], [14] has demonstrated success in detecting diseases and pests, it often focuses on specific algorithms or utilizes limited datasets available for potato leaves. Furthermore, most studies, such as those [15], [16], [17], do not compare multiple algorithms directly within the same context, which is a gap in the existing research.

To address existing research gaps, this investigation evaluates the comparative efficacy of four computational frameworks, Random Forest, XGBoost, SVM, and CNN, in diagnosing potato leaf pathologies using an expanded and heterogeneous dataset. Beyond basic accuracy, the methodological approach incorporates a multi-dimensional performance assessment, utilizing metrics such as precision, recall, and F1-score to delineate the specific strengths and operational constraints of each architecture. Consequently, this study provides significant academic and practical insights into automated phytopathology detection, offering a more nuanced benchmarking of algorithms against highly diverse image data.

Method

Research protocol

This investigation delineates a comparative study of supervised learning and neural network models in the context of plant pathology detection. The primary objective is to evaluate the performance of Random Forest, XGBoost, SVM, and CNN in classifying potato leaf conditions. The operational protocol is organized into distinct functional blocks: data procurement, image preprocessing, and sample splitting, followed by model optimization and cross-validation. The final phase involves a performance benchmarking analysis to derive meaningful insights. A schematic overview of the integrated research methodology is provided in Figure 1.

Dataset

The dataset used in this study was obtained from the website https://www.kaggle.com, which consists of 1,000 images of Potato Early Blight (leaf spots), 152 images of Potato Healthy (healthy leaves), and 1,000 images of Potato Late Blight (leaf rot). Additional data was collected through new image captures to supplement the testing data, consisting of 120 images, with 40 images each for leaf spots, leaf rot, and healthy leaves. Table 1 presents the example dataset of the study.

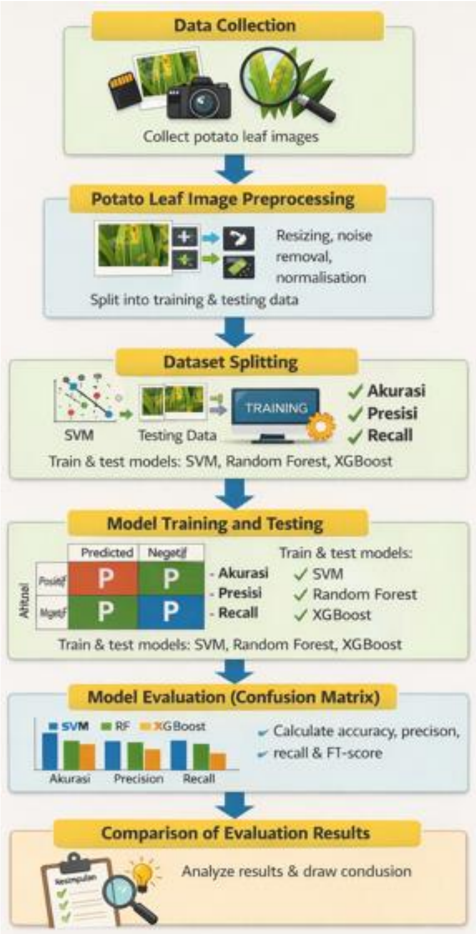

Figure 1. Research methodology

Table 1. Example dataset of the study

No	Leaf Images	Description
1		Early_Blight
2		Early_Blight
3		Early_Blight
4		Late_Blight
5		Late_Blight
6		Late_Blight
7		Healty
8		Healty
9		Healty

Preprocessing

Before the dataset is used, the initial step involves preprocessing. This process includes resizing and rescaling. Resize is the process of changing the dimensions (height and width) of an image to meet a desired size without considering the pixel scale of the image. In the context of images, this means reducing or enlarging the image to achieve a specific size (e.g., 256x256 pixels or 128x128 pixels). The purpose of resizing is to standardize the image size, making it more efficient for processing by the model, helping reduce computational load, speed up the model's training time, and align the image size with the expected input of the model [18]. On the other hand, rescaling is the process of changing the pixel value scale of an image without altering the image's dimensions. Both resizing and rescaling are crucial in data preparation for machine learning or deep learning models to ensure that the model can operate effectively and efficiently [18].

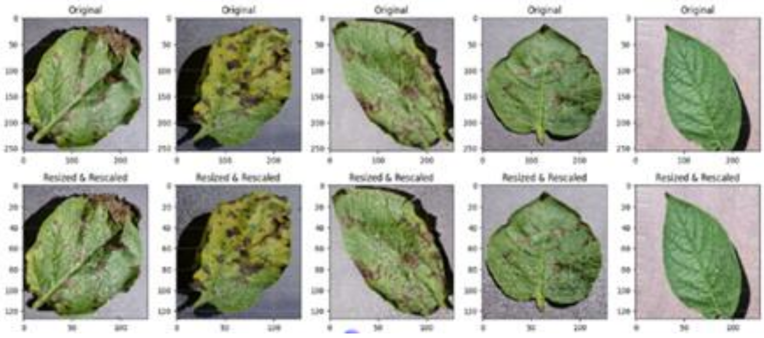

Figure 2. Process resize dan rescaled

The image displays two rows of pictures showing potato leaves, highlighting the difference between the original (raw) image and the resized & rescaled image. The first row shows the leaf in its original form, sized 256x256, while the second row shows the leaf after undergoing the resizing process to 128x128 and rescaling (pixel scale adjustment), resulting in changes to the size and aspect ratio of the image. The process of resize and rescaled show in Figure 2.

Support Vector Machine (SVM)

In the context of predictive modeling, Support Vector Machine (SVM) functions by establishing a separating hyperplane that maximizes the distance between binary or multiple classes. The methodology centers on the concept of margin, the spatial gap between the hyperplane and the closest training observations. These influential data points, known as support vectors, are the primary determinants of the hyperplane's orientation and position. By maximizing this interval, SVM reduces structural risk and improves classification robustness, making it a highly effective tool for high-dimensional pattern recognition. The formula for finding the hyperplane is as follows:

$$w \, . \, x + b = 0 \qquad (1)$$

Where: w = is the vector normal to the hyperplane d; b = bias. SVM seeks to find w dan b that maximize the margin, which can be calculated using the following formula:

$$Margin = \frac{2}{||w||} \tag{2}$$

The objective of optimization is to maximize the margin, which can be achieved by minimizing the objective function:

$$Min\ \frac{1}{2}\ ||w||^2 \tag{3}$$

With the constraint for each data point:

$$yi(w\ .xi\ +\ b) \geq 1, i\ = 1, 2, \ldots n$$

Random forest

The Random Forest algorithm represents a sophisticated application of bootstrap aggregation applied to decision tree architectures. By constructing an ensemble of independent learners, the model achieves high predictive accuracy through collective decision-making, either via majority vote or ensemble averaging. Its structural integrity relies on stochastic data sampling (bootstrapping) to ensure training diversity and randomized attribute selection at each decision node. This methodology ensures that the resulting forest remains resilient to noise and exhibits superior generalization capabilities compared to single-tree models. The main formula in random forest:

$$\hat{Y} = \text{mode}\ (\ \hat{Y}_1, \hat{Y}_2, \ldots, \hat{Y}_n) \tag{4}$$

Where: $\hat{Y}i$ = Prediction result from the i tree; mode = The value that appears most frequently. In this way, random forest reduces the likelihood of overfitting that can occur in a single decision tree, making it more robust and accurate.

XGBoost (extreme gradient boosting)

XGBoost is a highly popular machine learning algorithm, especially in data science competitions, due to its ability to handle various classification and regression problems with high accuracy. XGBoost is an implementation of gradient boosting that focuses on speed and efficiency. Formula in XGBoost:

1. Suppose we have a model consisting of a series of decision trees f1(x),f2(x),…,fT(x)

   $$\hat{y}\ \sum_{t=1}^{T} ft(x) \tag{5}$$

   Where: ft(x) = Prediction result of the t-th tree

2. In XGBoost, we optimize the loss function to improve predictions:

   $$\mathcal{L}(\theta) = \sum_{i=1}^{N} \ell(yi, \hat{y}i) + \sum_{t=1}^{T} \Omega\ (ft) \tag{6}$$

   Where: l(Yi,Yˆi) = The loss function that measures the error between the prediction (Yi)ˆ and the actual value Yi; Ω(ft) = Regularization that controls the model complexity (e.g., to prevent overfitting).

Convolutional Neural Network (CNN)

Designed to transcend the limitations of standard MLPs in processing spatial data, CNNs utilize a layered architecture to interpret complex visual patterns. The primary phase involves convolutional operations, where learnable filters are applied across the input to generate feature maps. To mitigate computational complexity and prevent overfitting, pooling or downsampling layers are strategically employed to condense the data representation while preserving salient information. In the final stage, the network utilizes fully connected (dense) layers to synthesize these high-level features into categorical outputs, facilitating accurate class prediction [19].

Results and Discussion

Training and testing

The training phase was executed to enable the models to capture essential data characteristics, utilizing a split-dataset approach for training and evaluation. The study benchmarked Random Forest, SVM, XGBoost, and VGG16-based CNN architectures.

First, the Random Forest classifier demonstrated a significant training accuracy of 97.7%, reflecting successful optimization on the primary dataset. Validation and testing accuracies were balanced at 82% and 82.3%, respectively; this marginal discrepancy underscores the model's stability and its resilience against overfitting. To further assess performance, Figure 2 illustrates the learning curve, providing insights into the correlation between training volume and predictive accuracy, with comprehensive results summarized in Table 2.

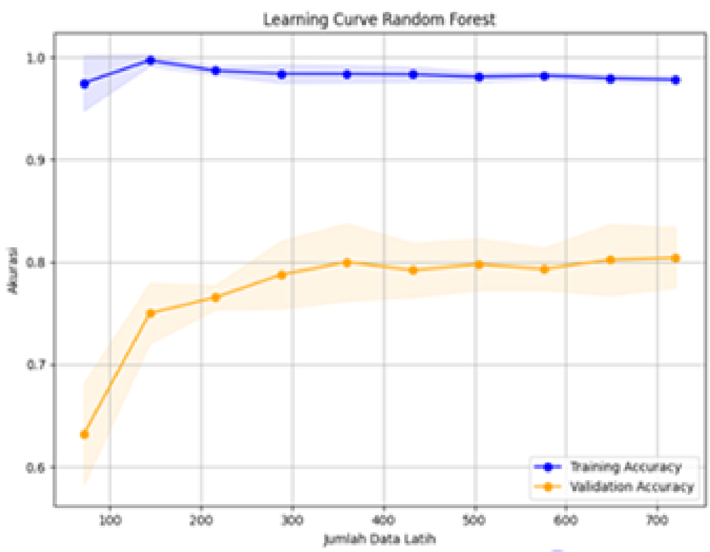

Figure 3. Learning curve random forest

Table 2. Random forest classification results

Class	Precision	Recall	F1-Score	Support
Potato Early_Blight	0.92	0.87	0.89	100
Potato Late_Blight	0.79	0.8	0.8	100
Potato Healthy	0.77	0.8	0.78	100
Accuracy	0.82	0.82	0.82	300

Second, support vector machine's model. Support vector model produces a learning curve shown in Figure 4 that illustrates the relationship between dataset size and model performance, which is favorable.

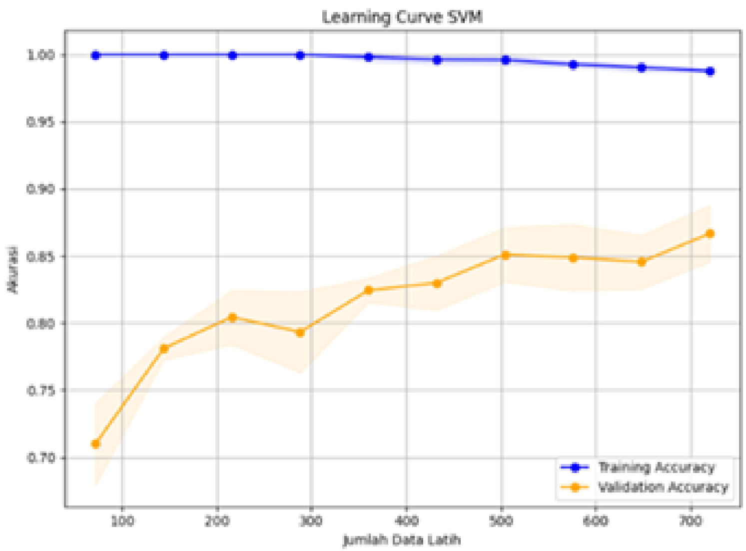

Figure 4. Learning Curve SVM

The SVM model demonstrates excellent performance across all classes (early blight, late blight, and healthy). The overall accuracy of the model is 89%, which is a strong result. The Healthy class shows the best performance with a perfect balance of precision and recall, while the Late Blight class has slightly lower precision but a higher recall. The Early Blight class shows good performance with an F1-score of 0.91 (Table 3).

Table 3. Random forest classification results

Class	Precision	Recall	F1-Score	Support
Potato Early_Blight	0.93	0.87	0.90	100
Potato Late_Blight	0.81	0.86	0.83	100
Potato Healthy	0.93	0.93	0.93	100
Accuracy			0.91	300

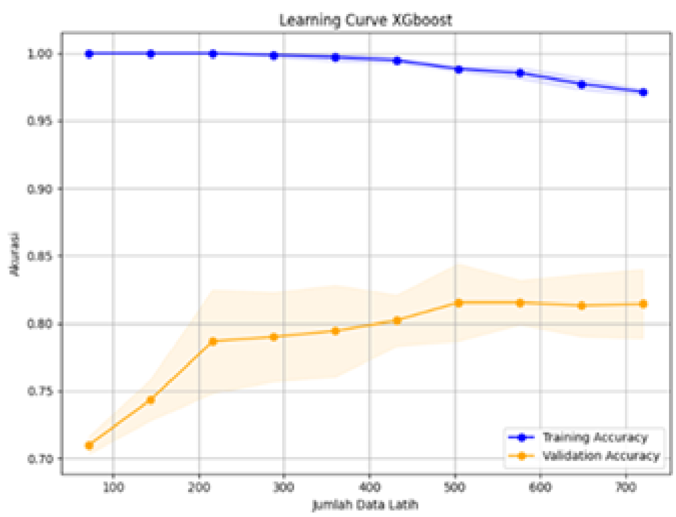

Figure 5. Learning Curve XGBoost

Third, XGBoost's model. The training and testing process on the XGBoost model was conducted to determine the values of Training Accuracy, Validation Accuracy, and Test Accuracy. The training results can be seen in the following learning curve image Figure 5.

The testing results show that the XGBoost model performs well with a good balance between training and generalization. The training accuracy reached 95.56%, demonstrating the model's ability to recognize data patterns very well. The validation accuracy of 84.67% indicates that the model can adapt to new data without significant overfitting. Meanwhile, the test accuracy of 85.33% shows consistent performance on data that was not involved in the training. Overall, XGBoost proves to be robust and effective in classifying potato leaf diseases based on image data in Table 4.

Tabel 4. XGBoost Classification Results

Class	Precision	Recall	F1-Score	Support
Potato Early_Blight	0.92	0.88	0.90	100
Potato Late_Blight	0.82	0.81	0.81	100
Potato Healthy	0.83	0.87	0.85	100
Accuracy			0.85	300

Overall, the XGBoost model demonstrates good performance with an accuracy of 85%. The Potato_Early_blight class performs very well with an F1-Score of 0.90, while the Potato_Late_blight class is slightly weaker with an F1-Score of 0.81. Although there is a small difference in performance between these classes, the model is fairly consistent in classifying all three classes effectively.

The fourth architecture evaluated was the Convolutional Neural Network (CNN) integrated with the VGG16 framework. Upon completion of the training and validation phases, the model demonstrated superior generalization capabilities, reaching an aggregate accuracy of 96% on the independent test set. A granular analysis of class-specific performance reveals that for 'Potato Early Blight,' the model achieved a precision of 1.00 and a recall of 0.95, culminating in an F1-score of 0.97. Similarly, the 'Potato Late Blight' category exhibited robust metrics with a precision of 0.92 and a recall of 0.97, resulting in an F1-score of 0.94. These findings, as summarized in Table 5, validate the proficiency of the VGG16-based CNN in classifying phytopathological conditions even when faced with high image complexity.

Tabel 5. CNN with The VGG16 Classification Results

Class	Precision	Recall	F1-Score	Support
Potato Early_Blight	1.00	0.95	0.97	100
Potato Late_Blight	0.92	0.97	0.94	100
Potato Healthy	0.97	0.96	0.97	100
Accuracy			0.96	300

Testing on new data

Testing on unseen data is essential in machine learning to evaluate a model's ability to generalize beyond the training dataset. Without such testing, performance is measured only on known data, increasing the risk of overfitting, where the model fits the training data too closely and fails to perform well on new data. Testing on new data also aims to evaluate accuracy, precision, recall, F1-score, or other metrics on a representative dataset, rather than just the training or validation data used in the tuning process. This provides a more realistic view of how the model will perform in real-world scenarios [20]. Testing with new data, which may have different characteristics (such as noise, changing distributions, or more challenging data), helps assess how robust the model is. A good model should still perform well even when faced with imperfect data or data from a slightly different domain [21].

Figure 6. New data testing for random forest

Figure 6 presents the random forest prediction results on potato leaf images affected by Early Blight. Each image displays the actual label, predicted label, and confidence score. Although the leaves show Early Blight symptoms, the model misclassifies them as healthy with confidence values of 45.28%, 38.64%, and 40.12%, indicating difficulty in distinguishing diseased from healthy leaves.

Figure 7. New data testing for XGBoost

Figure 7 shows XGBoost prediction results for potato leaves affected by Late Blight. The first two images are correctly classified as Late Blight with confidence scores of 80.74% and 59.84%, respectively. However, the third image is misclassified as Healthy with a confidence of 59.86%, indicating a limitation of the model in distinguishing infected from healthy leaves in certain cases, despite its generally reliable performance.

Figure 8. New Data Testing for SVM

Figure 8 presents three potato leaves affected by Late Blight and classified using the Support Vector Machine (SVM) model. Each image includes the predicted class and confidence score. The first leaf shows the highest confidence (99.69%), while the second and third leaves have lower confidence levels of 87.88% and 83.77%, indicating greater classification uncertainty. Overall, these results demonstrate the SVM model's ability to identify potato leaf diseases with varying confidence levels.

Figure 9. New Data Testing for CNN with The VGG16

The experimental results in Figure 9 demonstrate that the VGG16-based CNN model correctly classified all tested samples as Potato_healthy, with predictions fully aligned with the ground truth labels. The confidence scores were notably high, reaching 99.58%, 88.13%, and 100.00%, respectively. These findings indicate that the proposed model exhibits strong discriminative capability and reliable prediction performance in identifying healthy potato leaf images under the evaluated test conditions.

Performance evaluation

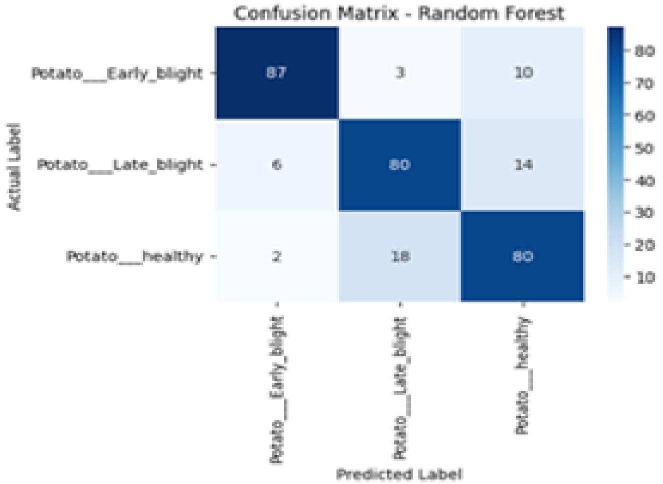

Figure 10. Random Forest Model Confusion Matrix Evaluation

The performance evaluation of each model, Random Forest, SVM, XGBoost, and CNN can be seen based on the analysis of the Confusion Matrix. Figure 10 presents Random Forest model demonstrates fairly good performance, as indicated by the higher values on the diagonal compared to the non-diagonal values. The model has a low overall error rate, with only a few misclassifications, such as 10 instances incorrectly classified as Potato_Early_blight and 14 as Potato_Late_blight. However, the model still makes errors in the Potato_Healthy category, with 18 instances misclassified.

Figure 11 presents SVM demonstrates performance similar to that of Random Forest and XGBoost, with high accuracy, especially in the Potato_Healthy category (93). The model also makes errors in the Potato_Early_blight category (13 misclassifications) and the Potato_Late_blight category (7 misclassifications). However, overall, SVM shows very good performance, particularly in the Healthy category.

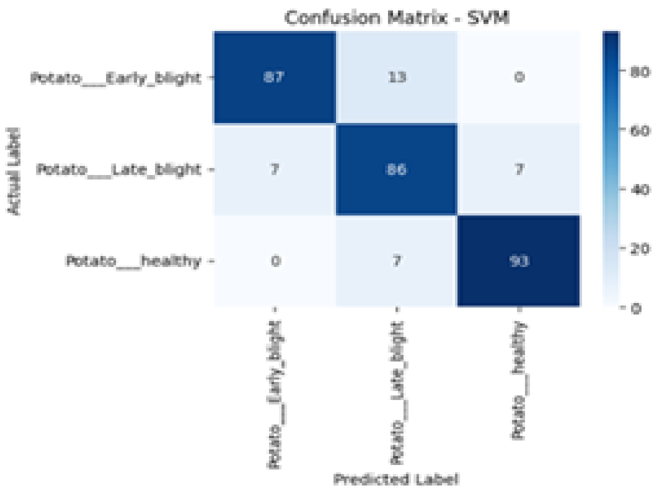

Figure 11. SVM Model Confusion Matrix Evaluation

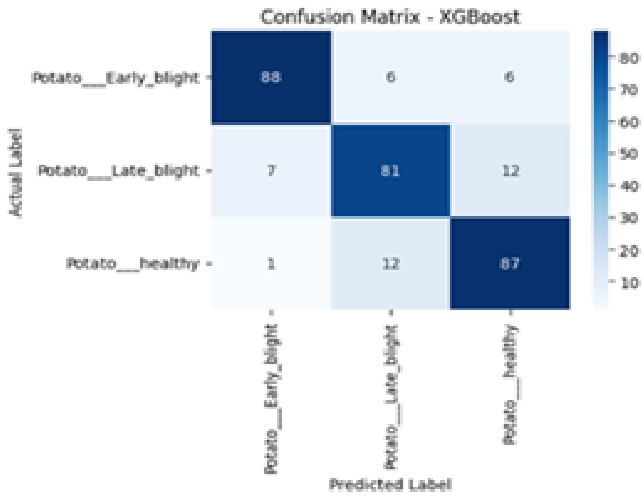

Figure 12. XGBoost Model Confusion Matrix Evaluation

XGBoost demonstrates strong performance, with most predictions correctly aligned along the diagonal, although some misclassifications persist, particularly in the Potato_Late_blight class (Figure 12). Overall, the three models exhibit comparable accuracy with slight class-specific differences: SVM performs best in the Potato_Healthy class, Random Forest shows more balanced error distribution across classes, and XGBoost performs well but produces relatively more misclassifications in the Potato_Late_blight class. Figure 12 presents XGBoost Model Confusion Matrix Evaluation.

Figure 13 presents the confusion matrix illustrates the classification performance of the proposed CNN with VGG16 model across three classes: Potato_Early_blight, Potato_Late_blight, and Potato_healthy. The model correctly classified 95 Early Blight samples, 97 Late Blight samples, and 96 Healthy samples, indicating strong overall predictive capability. Misclassifications were minimal, with a small number of Early Blight samples incorrectly predicted as Late Blight (5 cases), Late Blight as Healthy (3 cases), and Healthy as Late Blight (4 cases). Overall, the confusion matrix confirms the robustness and high classification accuracy of the model in distinguishing between visually similar potato leaf disease categories. Overall, the performance of the four models is presented in the Table 6.

Figure 13. CNN with VGG16 Model Confusion Matrix Evaluation

Table 6. Model comparison

Model	accuracy	advantages	Disadvantages
Random Forest	0.82	Stable & balanced across classes	Sensitive to outliers
SVM	0.91	High accuracy	Requires kernel parameter tuning
XGBoost	0.85	Efficient & fast	Slight risk of overfitting
CNN with VGG16	0.96	High predictive performance	High computational complexity

Conclusion

Based on the results of the research conducted, the four models were able to classify potato leaf diseases effectively. Each model has its own strengths and weaknesses. The comparative evaluation demonstrates that the CNN with VGG16 outperformed the Random Forest, SVM, and XGBoost models in potato leaf disease classification. While SVM achieved strong and balanced performance (0.91 accuracy), and XGBoost and Random Forest produced satisfactory results (0.85 and 0.82 accuracy, respectively), the VGG16-based CNN obtained the highest overall accuracy of 0.96 with consistently superior precision, recall, and F1-scores across all classes. This indicates that deep learning models provide more powerful feature extraction and discriminative capability for image-based plant disease detection. However, despite its superior performance, the VGG16 model has limitations, including high computational complexity and large parameter size, which may restrict its deployment in resource-constrained environments. In contrast, traditional machine learning models such as SVM, Random Forest, and XGBoost are computationally more efficient and easier to implement, although they generally offer lower classification accuracy compared to deep learning approaches. These results are in line with previous research [4] [13] Future studies are encouraged to expand the dataset and incorporate a wider variety of disease classes to enhance model robustness and generalization performance.

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References

1. M. J. Setiawan, Budi Nugroho, and Anggraini Puspita Sari, "Klasifikasi Penyakit Daun Tanaman Menggunakan Algoritma CNN dan Random Forest," *Teknologi*, vol. 13, no. 2, pp. 12–18, Jul. 2023, doi: 10.26594/teknologi.v13i2.3739.
2. A. Rahman, D. Udjulawa, and M. Mulyati, "Rekomendasi Pemilihan Jenis Tanaman Menggunakan Algoritma Random Forest dan XGBoost Regressor," *Computer Science (CO-SCIENCE)*, vol. 4, no. 2, pp. 119–126, Jul. 2024, doi: 10.31294/coscience.v4i2.2987.
3. A. Rahman, D. Udjulawa, and M. Mulyati, "Rekomendasi Pemilihan Jenis Tanaman Menggunakan Algoritma Random Forest dan XGBoost Regressor," *Computer Science (CO-SCIENCE)*, vol. 4, no. 2, pp. 119–126, Jul. 2024, doi: 10.31294/coscience.v4i2.2987.
4. P. T. U. Prasetyo, B. Santoso, and S. Kacung, "Sistem Deteksi Penyakit Pada Daun Tanaman Kentang Menggunakan Metode CNN Arsitektur VGG-Net," *Jurnal Informatika Teknologi dan Sains (Jinteks)*, vol. 7, no. 2, pp. 777–784, May 2025, doi: 10.51401/jinteks.v7i2.5758.
5. M. De Silva and D. Brown, "Multispectral Plant Disease Detection with Vision Transformer–Convolutional Neural Network Hybrid Approaches," *Sensors*, vol. 23, no. 20, p. 8531, Oct. 2023, doi: 10.3390/s23208531.
6. S. Hadianti, F. Aziz, D. Nur Sulistyowati, D. Riana, R. Saputra, and Kurniawantoro, "Identification of Potato Plant Pests Using the Convolutional Neural Network VGG16 Method," *Journal Medical Informatics Technology*, pp. 39–44, Jun. 2024, doi: 10.37034/medinftech.v2i2.37.
7. S. M. Alhammad, D. S. Khafaga, W. M. El-hady, F. M. Samy, and K. M. Hosny, "Deep learning and explainable AI for classification of potato leaf diseases," *Front. Artif. Intell.*, vol. 7, Feb. 2025, doi: 10.3389/frai.2024.1449329.
8. Z. Li and S. M. Javidan, "ML-based approach to potato diseases diagnosis using image processing and whale optimization algorithm for feature selection," *Smart Agricultural Technology*, vol. 12, p. 101282, Dec. 2025, doi: 10.1016/j.atech.2025.101282.
9. Erlin, I. Fuadi, R. N. Putri, D. Nasien, Gusrianty, and D. Oktarina, "Deep Learning Approaches for Potato Leaf Disease Detection: Evaluating the Efficacy of Convolutional Neural Network Architectures," *Revue d'Intelligence Artificielle*, vol. 38, no. 2, pp. 717–727, Apr. 2024, doi: 10.18280/ria.380236.
10. T. Astuti, A. N. Umar, R. Wahyudi, and Z. Rifai, "Enhancing Potato Leaf Disease Detection: Implementation of Convolutional Vision Transformers with Synthetic Datasets from Stable Diffusion," *JOIV : International Journal on Informatics Visualization*, vol. 8, no. 4, p. 2054, Dec. 2024, doi: 10.62527/joiv.8.4.2167.
11. Md. A. Islam and Md. H. Sikder, "A Deep Learning Approach to Classify the Potato Leaf Disease," *Journal of Advances in Mathematics and Computer Science*, pp. 143–155, Dec. 2022, doi: 10.9734/jamcs/2022/v37i121735.
12. A. Ikhwan, N. A. Bi Rahmani, M. H. Aly, N. Aslami, M. Dedi Irawan, and I. Ahmad, "Application Of Expert System In Determining Diseases In Potato Plants," *Indonesian Journal of Information Systems*, vol. 7, no. 2, pp. 194–203, Feb. 2025, doi: 10.24002/ijis.v7i2.10213.
13. P. Teresia Ompusunggu, "Klasifikasi Penyakit Tanaman Pada Daun Kentang Dengan Metode Convolutional Neural Network Arsitektur Mobilenet," *Jurnal Syntax Fusion*, vol. 2, no. 09, pp. 740–751, Sep. 2022, doi: 10.54543/fusion.v2i09.217.
14. V. Riyanto, S. Nurdiati, M. Marimin, M. Syukur, and S. N. Neyman, "Deep Learning Approaches for Plant Disease Diagnosis Systems: A Review and Future Research Agendas," *Journal of Applied Agricultural Science and Technology*, vol. 9, no. 2, pp. 185–204, May 2025, doi: 10.55043/jaast.v9i2.308.
15. Y. Zhao, C. Sun, X. Xu, and J. Chen, "RIC-Net: A plant disease classification model based on the fusion of Inception and residual structure and embedded attention mechanism," *Comput. Electron. Agric.*, vol. 193, p. 106644, Feb. 2022, doi: 10.1016/j.compag.2021.106644.

16. G. Singh, G. Kasana, and K. Singh, “Improved Potato Crop Disease Classification Using Ensembled Convolutional Neural Network,” *Potato Res.*, vol. 68, no. 2, pp. 1501–1527, Jun. 2025, doi: 10.1007/s11540-024-09787-0.
17. B. Gülmez, “A Comprehensive Review of Convolutional Neural Networks based Disease Detection Strategies in Potato Agriculture,” *Potato Res.*, vol. 68, no. 2, pp. 1295–1329, Jun. 2025, doi: 10.1007/s11540-024-09786-1.
18. F. Chollet, *Deep learning with Python*. Manning, 2018.
19. Ian. Goodfellow, Yoshua. Bengio, and Aaron. Courville, *Deep learning*. The MIT Press, 2017.
20. Joel. Grus, *Data science from scratch : first principles with Python*. O’Reilly, 2015.
21. Sebastian. Raschka and Vahid. Mirjalili, *Python machine learning : machine learning and deep learning with python, scikit-learn, and tensorflow 2*. Packt Publishing, Limited, 2019.