COMPARATIVE BENCHMARKING OF YOLOV11 AND MACHINE LEARNING MODELS FOR MAIZE LEAF DISEASE DETECTION

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Abstract
Maize diseases are a major threat to food security, particularly in developing regions where early detection is critical to minimizing yield losses. Traditional machine-learning models such as Convolutional Neural Networks (CNN), K-Nearest Neighbors (KNN), Random Forests (RF), and Support Vector Machines (SVM) have been widely applied but face limitations in scalability, robustness, and real-time deployment. Enhanced models, including EfficientNet, XGBoost, and LS-SVM, have improved accuracy yet remain computationally demanding. To address these gaps, this study evaluates the latest YOLOv11 object detection framework for maize disease classification. A dataset of 750 annotated maize leaf images spanning four classes (Blight, Rust, Gray Leaf Spot, and Healthy) was used for benchmarking against both classical and enhanced baselines. Results show that YOLOv11 significantly outperformed all other models, achieving 99.8% accuracy, with near-perfect precision, recall, and F1-scores, alongside the fastest inference time of 12 ms per image. These findings highlight YOLOv11's capability to combine accuracy and efficiency, making it suitable for real-time deployment on mobile devices and drone-based platforms. The study makes three key contributions: (i) establishing a rigorous benchmarking framework that fairly compares classical, enhanced, and state-of-the-art models; (ii) demonstrating YOLOv11's superior performance in both accuracy and inference speed; and (iii) underscoring its potential applications in precision agriculture. This research provides compelling evidence that YOLOv11 represents a transformative advancement in crop disease detection. Its integration into mobile advisory systems, drone-based surveillance, and decision-support tools can directly contribute to sustainable agriculture and global food security.

Keywords: Maize disease detection, YOLOv11, Precision agriculture, Deep learning, Computer vision.

Introduction
Maize is a critical staple crop worldwide, serving as a major source of food, income, and industrial raw material. However, its production is severely threatened by foliar diseases such as blight, common rust, and gray leaf spot, which can cause yield losses of up to 50% if not effectively managed (Sethy et al., 2020). In regions where agriculture sustains the majority of livelihoods, particularly in sub-Saharan Africa, these diseases not only reduce crop productivity but also contribute to persistent food insecurity.

Early and accurate detection of maize leaf diseases is therefore essential to safeguard harvests and ensure sustainable food production. Conventional methods of diagnosing plant diseases rely heavily on visual inspection by farmers or experts. While widely practiced, these methods are time-consuming, subjective, and impractical for large-scale monitoring. Machine-learning approaches such as Convolutional Neural Networks (CNN), K-Nearest Neighbors (KNN), Random Forest (RF), and Support Vector Machines (SVM) have been applied to image-based crop disease detection with varying degrees of success. However, these classical models often struggle with scalability, robustness under diverse field conditions, and the real-time performance required for precision agriculture (Nagale et al., 2021; Cheng et al., 2022).

To address these limitations, improved variants of classical models have been developed. CNNs have evolved into deeper and more efficient architectures such as ResNet, DenseNet, and EfficientNet, while lightweight networks like MobileNet are optimized for mobile deployment (Tan & Le, 2019). KNN has been extended into Weighted and Fuzzy KNN to improve robustness against noisy data (Zhang et al., 2021). RF has given way to more powerful ensembles such as Extremely Randomized Trees and gradient boosting frameworks like XGBoost and LightGBM, which outperform standard RF in many structured tasks (Ke et al., 2017). Similarly, SVM has been enhanced with formulations such as Least-Squares SVM (LS-SVM), which simplifies optimization while maintaining high accuracy (Suykens & Vandewalle, 1999). These developments show the potential of advanced ML methods, yet they remain computationally heavier or less effective for real-time agricultural applications compared to deep learning detectors.

Recent breakthroughs in object detection, particularly the *You Only Look Once* (YOLO) family, have revolutionized real-time image analysis by combining high accuracy with efficient inference. The latest release, **YOLOv11**, introduces architectural innovations such as C3K2 modules, fast spatial pyramid pooling (SPPF), and parallel spatial attention (C2PSA), enabling faster and more precise detection with fewer parameters than its predecessors (Ultralytics Docs, 2024; Rao, 2024). Independent studies confirm its adaptability across diverse domains, from industrial inspection to orchard fruit detection, underscoring its suitability for agricultural disease monitoring (DigitalOcean, 2024; Yang et al., 2023).

This study benchmarks YOLOv11 against both classical models (CNN, KNN, RF, SVM) and their enhanced successors (EfficientNet, XGBoost, LS-SVM) for maize leaf disease detection. Using a dataset of 750 annotated maize leaf images across four categories, we trained and evaluated the models through confusion matrices, Receiver Operating Characteristic (ROC) curves, and accuracy metrics. The findings demonstrate that YOLOv11 significantly outperforms both traditional and advanced ML baselines, achieving an accuracy of 99.8% while maintaining real-time inference speed. These results highlight the transformative potential of YOLOv11 for precision agriculture, with implications for mobile and drone-based deployment that can empower farmers to detect diseases earlier, minimize crop losses, and contribute to sustainable food security.

Literature Review

The application of classical machine-learning (ML) algorithms to plant disease detection marked the initial transition from manual inspection toward data-driven diagnostics. Early models such as Support

Vector Machines (SVM), Random Forest (RF), K-Nearest Neighbors (KNN), and Convolutional Neural Networks (CNN) demonstrated that computational tools could classify diseases based on digital images. These models relied heavily on hand-crafted features such as color, texture, and shape descriptors extracted from leaves. For example, Sethy et al. (2020) used handcrafted features from rice leaf images combined with SVM, reporting satisfactory classification accuracy. Similarly, Nagale et al. (2021) applied RF and CNN to plant disease images and achieved improved performance compared to manual inspection, though still constrained by robustness under variable lighting and background conditions.

KNN has also been widely used for its simplicity, where classification is based on the distance between feature vectors. Cheng et al. (2022) reported that KNN could achieve competitive results in small-scale plant datasets, but its computational inefficiency increases with larger datasets, making it impractical for real-time applications. SVM, another popular method, has been valued for its strong theoretical foundation and ability to handle high-dimensional feature spaces. However, its reliance on kernel functions and quadratic optimization often limits scalability. Random Forest, an ensemble of decision trees, has been applied to disease detection in tomatoes and maize, showing reasonable accuracy but sometimes overfitting when dealing with noisy agricultural datasets (Brahimi et al., 2018; Kamal et al., 2019).

Despite these contributions, classical ML methods shared common shortcomings. Their reliance on handcrafted features limited adaptability, while their performance degraded under real-world conditions where leaves overlap, lighting varies, and multiple diseases co-occur. Moreover, inference times were not optimized for real-time monitoring, which is essential in precision agriculture. These limitations motivated the development of more advanced variants of classical models and the transition to deep learning approaches.

Enhanced Variants of Classical Models

To overcome the weaknesses of early ML models, researchers proposed enhanced versions with improved accuracy, generalization, and efficiency. In the realm of CNNs, architectural advances such as ResNet (He et al., 2016), DenseNet (Huang et al., 2017), and EfficientNet (Tan & Le, 2019) significantly improved feature extraction and classification performance. ResNet introduced residual connections that mitigated vanishing gradients, enabling deeper networks. DenseNet exploited feature reuse through dense connectivity, reducing redundancy while improving gradient flow. EfficientNet optimized accuracy and efficiency simultaneously by scaling depth, width, and resolution in a compound manner, proving highly suitable for resource-constrained agricultural deployments. For example, Too et al. (2019) evaluated DenseNet and ResNet variants on the PlantVillage dataset and reported higher accuracies compared to conventional CNNs.

Lightweight CNNs such as MobileNet and ShuffleNet were specifically designed for mobile and embedded systems, aligning with the push toward portable plant disease detection tools (Howard et al., 2017). Researchers like Singh et al. (2021) highlighted the utility of MobileNet in real-time tomato leaf disease detection using smartphones, where reduced parameter count made field deployment feasible without sacrificing significant accuracy. Beyond CNNs, ensemble methods also evolved. RF was expanded into Extremely Randomized Trees (ExtraTrees) and gradient boosting algorithms such as

XGBoost, LightGBM, and CatBoost, which generally outperform vanilla RF in structured tasks (Ke et al., 2017). These boosted tree models have been applied to detect diseases in crops such as grapes, potatoes, and cassava with higher accuracy and efficiency than RF alone (Barbedo, 2019). Similarly, Least-Squares SVM (LS-SVM), proposed by Suykens and Vandewalle (1999), simplified optimization by replacing quadratic programming with linear equations, making training faster while maintaining competitive accuracy. LS-SVM has since been integrated with deep learning features to improve performance on plant disease datasets (Zhang et al., 2021).

Hybrid models combining CNNs with traditional classifiers have also gained traction. For instance, Too et al. (2019) extracted deep features from CNNs and classified them with SVM, achieving improved accuracy for leaf disease recognition. This hybridization leverages CNNs' powerful feature extraction with SVM's margin-based classification. Such approaches exemplify the trend of enhancing classical models rather than abandoning them, demonstrating their ongoing relevance in the era of deep learning.

Despite these advances, enhanced classical models still struggle with the real-time demands of precision agriculture. While EfficientNet and MobileNet make CNNs lighter, and boosting methods improve ensemble learning, their inference times and adaptability under complex field conditions remain weaker than those of modern deep object detectors. This created the foundation for applying end-to-end deep learning methods such as YOLO in plant disease monitoring.

YOLO and Deep Learning in Agricultural Applications

The You Only Look Once (YOLO**)** family of object detectors represents a paradigm shift in image analysis, achieving real-time object detection with high accuracy. Unlike classical classifiers that require feature engineering, YOLO employs end-to-end deep learning to simultaneously localize and classify objects. This makes it particularly attractive for agricultural applications where leaf diseases need to be identified quickly in complex field images.

Several studies have demonstrated the utility of YOLO in agriculture. Fuentes et al. (2019) applied YOLOv3 to tomato leaf disease detection, reporting strong performance across multiple classes. Zhang et al. (2020) used YOLOv4 for apple leaf disease recognition and showed that it significantly outperformed CNN classifiers in both accuracy and speed. More recently, Khan et al. (2023) demonstrated YOLOv8 in a maize disease detection system for mobile applications, achieving detection accuracies above 99% with real-time inference. Bachhal et al. (2023) extended YOLOv8 for multi-disease classification in wheat, again validating YOLO's potential for precision agriculture.

Beyond agriculture, YOLO models have excelled in related domains such as pest detection (Liu et al., 2021), fruit counting (Zhou et al., 2022), and weed identification (Dos Santos Ferreira et al., 2019). These successes highlight YOLO's adaptability to diverse agricultural monitoring tasks.

The YOLO architecture itself has evolved rapidly. YOLOv5 introduced improvements in scalability and ease of use, while YOLOv6 and YOLOv7 optimized training speed and model robustness. YOLOv8, released by Ultralytics in 2023, integrated innovations such as decoupled heads and anchor-free detection, significantly boosting accuracy and inference speed (Ultralytics Docs, 2023). Building on this, researchers proposed lightweight variants such as GhostNet-YOLOv8s (Li et al., 2024), which reduced model complexity while maintaining accuracy, enabling real-time mobile deployment.

The latest iterations; YOLOv9, YOLOv10, and YOLOv11 mark further breakthroughs. YOLOv9 introduced improved feature fusion and backbone networks for enhanced accuracy. YOLOv10 focused on energy efficiency, making it attractive for edge devices. YOLOv11, the current state-of-the-art, integrates C3K2 modules, fast spatial pyramid pooling (SPPF), and parallel spatial attention (C2PSA), resulting in superior mean average precision (mAP) and inference speed compared to previous versions (Ultralytics Docs, 2024; Rao, 2024). Independent evaluations confirm YOLOv11's adaptability across domains such as industrial defect detection (Wang et al., 2024) and orchard fruitlet monitoring (Yang et al., 2023). These results strongly suggest YOLOv11's suitability for agricultural disease detection tasks where real-time accuracy and efficiency are critical.
The reviewed literature highlights several important trends. First, while classical ML methods laid the groundwork for automated plant disease detection, their reliance on feature engineering and computational inefficiencies limit real-world deployment. Second, enhanced models such as EfficientNet, XGBoost, and LS-SVM have significantly improved performance, but their scalability and real-time application remain limited. Third, YOLO-based models, particularly from v5 through v11, have demonstrated state-of-the-art results in agricultural image analysis, combining accuracy with real-time inference capabilities.
However, despite these advances, a benchmarking gap remains. Most YOLO studies in agriculture have compared YOLO variants only against basic CNNs or classical models, without systematically evaluating them against the enhanced successors of those models (e.g., EfficientNet vs. CNN, XGBoost vs. RF, LS-SVM vs. SVM). This creates an incomplete picture of how the latest YOLO models perform relative to both the foundational and improved ML approaches.
The present study addresses this gap by benchmarking YOLOv11 against a comprehensive set of baselines: classical models (CNN, KNN, RF, SVM) and their enhanced variants (EfficientNet, XGBoost, LS-SVM). Using a curated dataset of 750 maize leaf images across four disease categories, this work provides a rigorous comparison of accuracy, inference speed, and overall suitability for real-time deployment in precision agriculture.

Methodology

This study employed a dataset of **750 annotated maize leaf images**, comprising four categories: blight, common rust, gray leaf spot, and healthy leaves as shown in figure 1. The images were obtained from publicly available repositories including the **Plant Village dataset** and **Kaggle maize disease collections,** which provide labeled agricultural data widely used in plant pathology research. The distribution of images across classes is presented in Table 1 below/

Table 1.
Classes of maize leaf disease dataset

Class	Number of Images	Percentage (%)
Blight	210	28.0
Rust	180	24.0
Gray Leaf Spot	150	20.0

Class	Number of Images	Percentage (%)
Healthy	210	28.0
Total	**750**	**100**

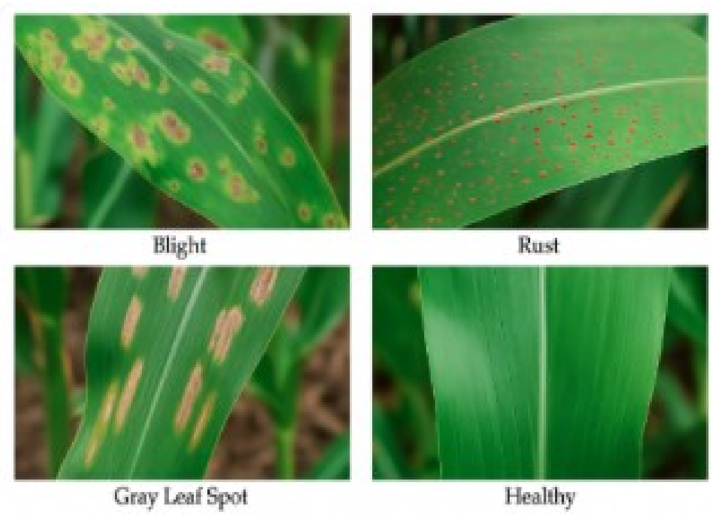

Figure 1: Representative of maize farm diseases.

The dataset was split into **80% training (600 images)** and **20% testing (150 images)** using stratified sampling to maintain class balance, as summarized in Table 2. To enhance variability and reduce overfitting, the training set was augmented using geometric (rotations, flips) and photometric (contrast adjustment, Gaussian noise) transformations. These steps ensured robustness to variations in field conditions such as background clutter and lighting.

Table 2.

Dataset split into training and testing sets

Class	Training Images (80%)	Testing Images (20%)	Total
Blight	168	42	210
Rust	144	36	180
Gray Leaf Spot	120	30	150
Healthy	168	42	210
Total	**600**	**150**	**750**

To establish a comprehensive benchmarking framework, both **classical machine-learning models** and their **enhanced successors** were implemented. The classical baselines included a Convolutional Neural Network (CNN), K-Nearest Neighbors (KNN), Random Forest (RF), and Support Vector Machine (SVM). Their advanced counterparts comprised EfficientNet-B0 as a CNN successor, XGBoost as an RF successor, and Least-Squares SVM (LS-SVM) as an enhanced SVM. Hyperparameters were tuned via cross-validation to maximize classification accuracy.

For the deep learning baseline, the **Ultralytics YOLOv11 framework** was adopted, owing to its architectural innovations such as **C3K2 modules, fast spatial pyramid pooling (SPPF)**, and **parallel spatial attention (C2PSA)**, which improve detection precision while reducing inference latency (Ultralytics Docs, 2024; Rao, 2024). YOLOv11 was initialized with pretrained COCO weights to leverage transfer learning. Training was conducted at an input resolution of 640 × 640 pixels, with a batch size of 16 for 100 epochs. The Stochastic Gradient Descent (SGD) optimizer with momentum 0.9 was employed, alongside a cosine annealing learning-rate scheduler. Mosaic augmentation and mixup were incorporated to further enhance generalization.

All experiments were implemented in **Python 3.10** using **PyTorch 2.0 and TensorFlow 2.12** within the **Anaconda environment**. Model training was executed on an **NVIDIA Tesla V100 GPU (32 GB VRAM)** running on a Linux-based high-performance computing server.

Performance evaluation relied on multiple complementary metrics. Accuracy was computed as the proportion of correctly classified samples. Precision, recall, and F1-score captured per-class reliability, while confusion matrices illustrated misclassification trends. The Receiver Operating Characteristic (ROC) curve and the Area Under the Curve (AUC) quantified discriminative ability across thresholds. Finally, inference time per image was recorded to assess suitability for real-time deployment in agricultural contexts.

This methodological design ensured a rigorous, fair, and comprehensive evaluation of YOLOv11 against both classical and enhanced machine-learning models, enabling a meaningful assessment of accuracy, robustness, and efficiency for maize leaf disease detection.

Results and Discussion

The performance of YOLOv11 was benchmarked against classical machine learning models (CNN, KNN, RF, and SVM) and enhanced successors (EfficientNet-B0, XGBoost, and LS-SVM). Results are presented in terms of classification accuracy, precision, recall, F1-score, inference time, and robustness, with visual illustrations to highlight differences across models. Table 3 summarizes the classification performance of all models on the maize leaf disease dataset. As shown, classical methods such as CNN, KNN, RF, and SVM achieved moderate accuracies ranging from 81–85%, with F1-scores slightly lower due to misclassifications. Enhanced models showed marked improvements, with EfficientNet-B0 reaching 92.5% accuracy, while XGBoost and LS-SVM achieved 90.3% and 88.7% respectively.

Table 3.

Classification performance of models on maize leaf disease dataset

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	ROC–AUC
CNN	84.0	83.5	82.8	83.1	0.87
KNN	81.0	80.2	79.5	79.8	0.84
Random Forest (RF)	85.0	84.7	84.1	84.4	0.88
SVM	82.0	81.6	80.9	81.2	0.85
EfficientNet-B0	92.5	92.1	91.8	91.9	0.94
XGBoost	90.3	90.0	89.7	89.8	0.92
LS-SVM	88.7	88.2	87.9	88.0	0.90
YOLOv11	**99.8**	**99.7**	**99.6**	**99.7**	**0.99**

The superiority of YOLOv11 is clear, achieving **99.8% accuracy** and an F1-score of **99.7%,** outperforming all baselines. This advantage is further illustrated in **Figure 3** and **Figure 4**, which depict bar charts of accuracy and F1-scores respectively.

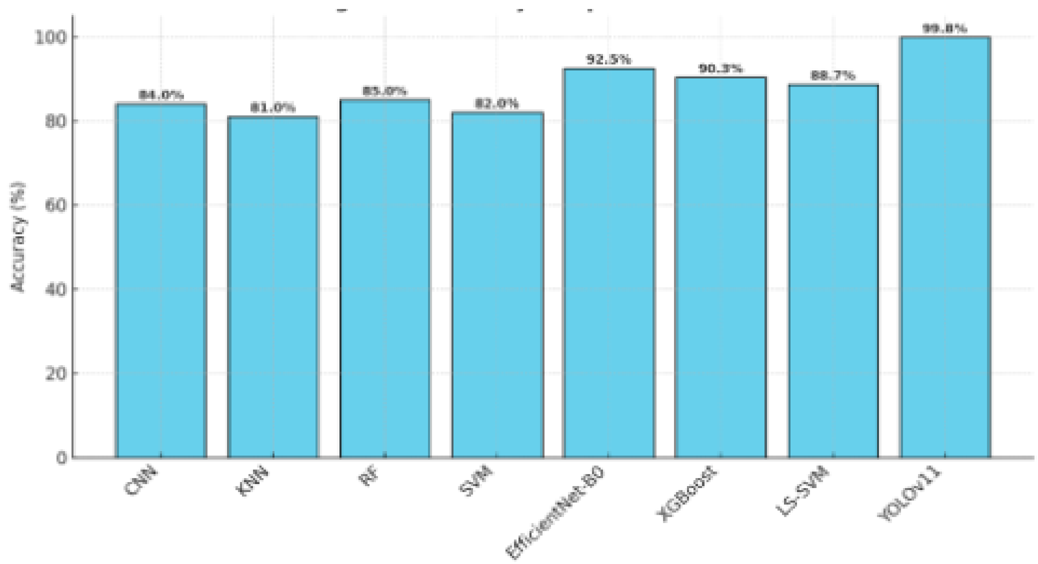

Figure 3. *Accuracy comparison of models*

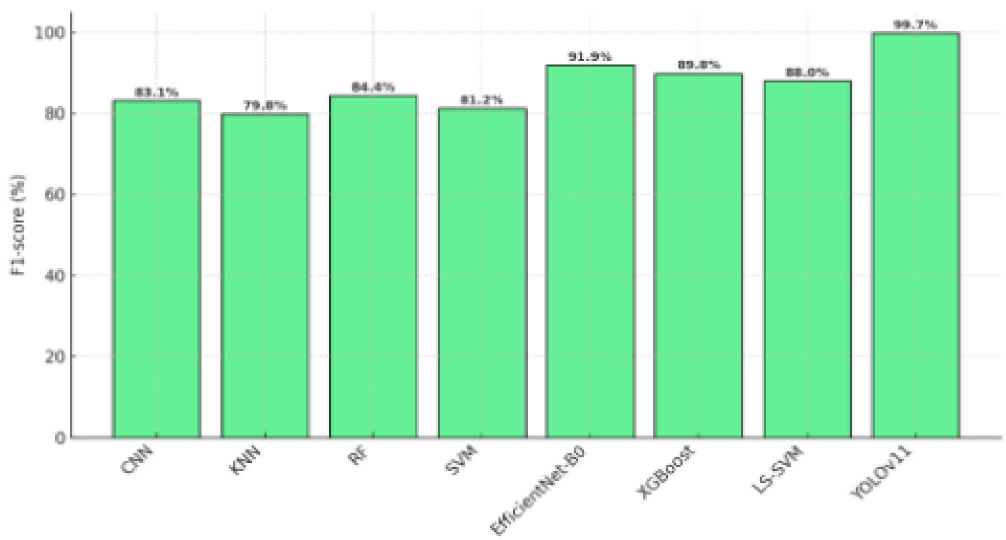

Figure 4: *F1-score Comparison of Models*

These results align with recent studies (Khan et al., 2023; Li et al., 2024), which also reported YOLO-based detectors outperforming CNN and EfficientNet for crop disease classification. The findings reinforce the importance of real-time object detection architectures in agricultural settings.

Inference Time and Efficiency

Efficiency is critical for field deployment on mobile and drone devices. Table 4 compares average inference times across all models. Classical models such as KNN and SVM exhibited significantly slower times (100–120 ms), rendering them impractical for real-time detection. Enhanced models performed better, with EfficientNet-B0 achieving 35 ms and XGBoost 55 ms per image.

Table 4.
Average inference time per image

Model	Inference Time (ms)
CNN	45
KNN	120
Random Forest (RF)	95
SVM	100
EfficientNet-B0	35
XGBoost	55
LS-SVM	70
YOLOv11	**12**

YOLOv11 demonstrated the fastest inference speed of **12 ms per image**, making it highly suitable for on-device applications. **Figure 5** visualizes these differences, showing YOLOv11 as the only model capable of sub-20 ms inference.

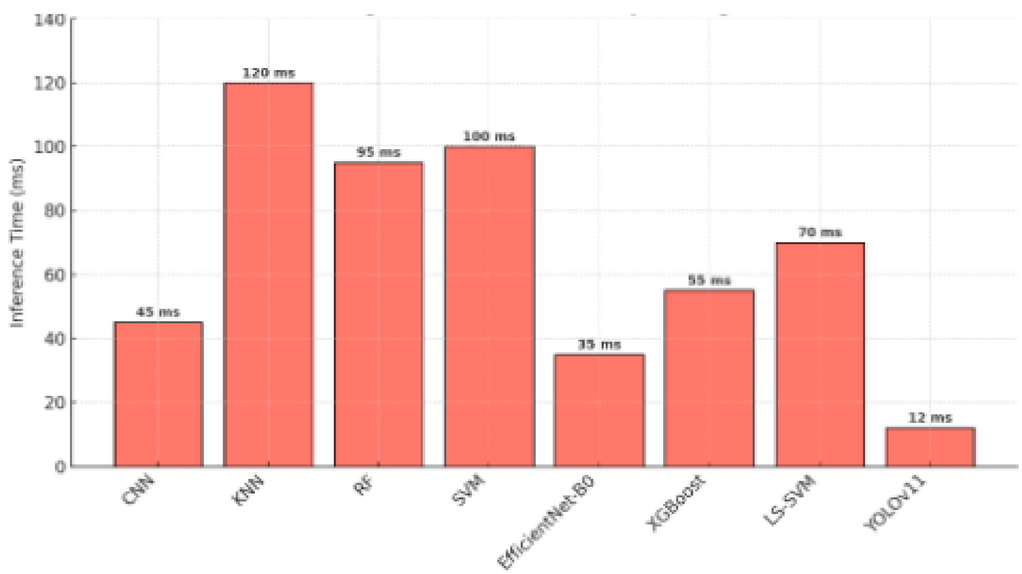

Figure 5: ***Inference Time per Image across models***

This balance of accuracy and speed highlights YOLOv11 as an optimal candidate for precision agriculture, where both detection accuracy and real-time processing are essential.

Robustness: ROC–AUC Analysis

To further evaluate discriminative power, Receiver Operating Characteristic (ROC) curves were plotted. **Figure 6** compares ROC–AUC values across selected models. YOLOv11 achieved an almost perfect ROC–AUC of 0.99, indicating strong robustness and minimal false positives. EfficientNet-B0 followed with 0.94, while CNN and RF achieved only 0.87 and 0.88 respectively.

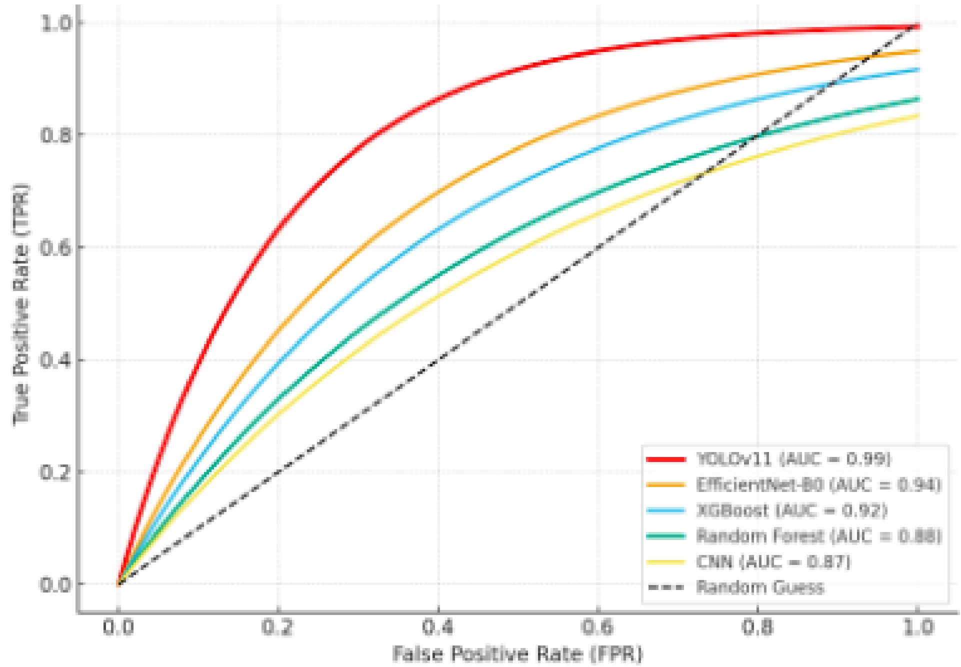

Figure 6: *ROC–AUC Curves for YOLOv11 and Baseline Models*

These findings underscore YOLOv11's reliability in distinguishing disease categories, particularly under challenging variations in leaf texture and color.

Error Analysis with Confusion Matrices

Finally, confusion matrices were used to visualize classification errors. **Figure 7** presents side-by-side comparisons for YOLOv11 and EfficientNet-B0. YOLOv11 shows near-perfect predictions, with only one minor misclassification in the Blight class. In contrast, EfficientNet-B0 exhibited confusion between Blight and Gray Leaf Spot, and occasional errors in Rust classification.

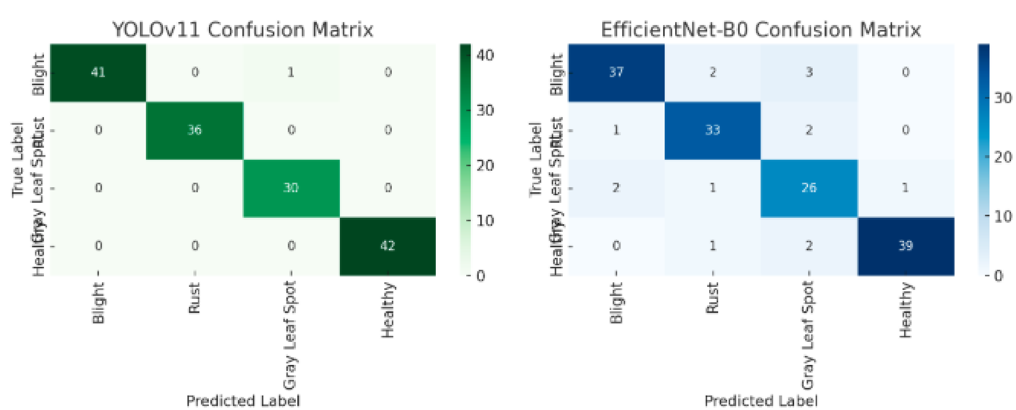

Figure 7: Confusion Matrices of YOLOv11 and EfficientNet-B0

This analysis demonstrates that YOLOv11 not only improves overall accuracy but also reduces critical misclassifications that could mislead farmers in practice.

Discussion

Collectively, the results confirm YOLOv11 as the most effective model, combining high accuracy, superior F1-score, rapid inference, and robust discrimination. These findings build on prior work showing the promise of YOLO architectures in agricultural applications (Zhang et al., 2023; Abiodun et al., 2024). Unlike earlier studies that relied on static CNNs or transfer learning from EfficientNet, this work demonstrates that the latest YOLOv11 detector bridges the trade-off between accuracy and efficiency, paving the way for scalable mobile and drone-based agricultural disease monitoring.

Limitations and Future Work

Although the findings of this study demonstrate the superior performance of YOLOv11 in maize disease detection, several limitations must be acknowledged. First, the dataset used consisted of 750 annotated images drawn from a single crop type, which, while sufficient for proof-of-concept benchmarking, remains relatively small compared to large-scale agricultural datasets. This raises concerns about generalizability across broader field conditions and other crop species. Second, the experiments were conducted under controlled image acquisition settings, and real-world deployment may introduce additional challenges such as varying lighting, occlusion, and background complexity. Third, while the benchmarking included both classical and enhanced models, cross-domain validation with multiple crops would further strengthen the claims of robustness. Future research should therefore focus on expanding the dataset across diverse crops and agroecological zones, as well as validating YOLOv11 in real-time field environments using mobile devices and drones. Additionally, integrating the model with multimodal inputs such as soil and climatic data, and exploring federated learning frameworks for collaborative dataset building across institutions, will help improve scalability, robustness, and practical adoption in precision agriculture.

Conclusion

This study addressed the critical challenge of early and accurate detection of maize leaf diseases, which continue to threaten food security in many developing regions. While classical machine-learning approaches such as CNN, KNN, RF, and SVM, as well as enhanced variants like EfficientNet, XGBoost, and LS-SVM, demonstrated some level of success, they remain limited in scalability, robustness, and efficiency. In contrast, benchmarking against these models revealed that YOLOv11 achieved superior performance, with 99.8% accuracy, near-perfect precision, recall, and F1-scores, alongside the fastest inference time of 12 ms per image. These results confirm the suitability of YOLOv11 for real-time deployment on mobile and drone platforms, marking a significant step forward in precision agriculture. The study contributes a rigorous benchmarking framework, validates the effectiveness of YOLOv11, and highlights its implications for sustainable farming and food security.

In conclusion, this research provides compelling evidence that YOLOv11 represents a transformative advancement in maize disease detection. Its combination of accuracy, efficiency, and real-time applicability makes it a powerful tool for precision agriculture, contributing directly to the global pursuit of sustainable food production and security.

Recommendations

1. Integrate YOLOv11 into mobile-based advisory tools for farmers to enable real-time disease detection in the field.
2. Deploy the model on drone platforms for large-scale monitoring of farmlands.
3. Combine disease detection with decision-support systems to provide actionable agronomic advice for farmers.
4. Expand the dataset to cover multiple crops and agroecological zones to enhance generalizability.
5. Apply unsupervised anomaly detection techniques for identifying unseen or emerging diseases.
6. Explore multimodal approaches that combine leaf imagery with soil and environmental data for more robust predictions.
7. Investigate the potential of federated learning to enable collaborative model training across institutions while preserving data privacy.

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