Early Detection of Oak Wilt Using Machine Learning and Unmanned Aerial Vehicles (UAVs)

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Abstract. Oak wilt, a highly contagious and lethal disease threatening oak trees across North America, has traditionally been detected through manual inspections, which are often time-intensive and insufficient for timely intervention. This study introduces an automated oak wilt detection system leveraging aerial imagery captured by unmanned aerial vehicles (UAVs) and a convolutional neural network (CNN) to classify environments as "Oak Wilt" or "Not Oak Wilt." The model, initially trained on a dataset of 271 oak wilt and 310 non-oak wilt images, was further refined with an expanded dataset of 1,051 images and tested on 9,981 images sourced from Lake Forest Cemetery State Park, Mulligan's Hollow State Park, P.J. Hoffmaster State Park, and Warren Dunes State Park.

A customized CNN architecture was developed, comprising three convolutional layers, three max-pooling layers, and fully connected layers. To enhance accuracy, the system incorporates data augmentation and geotagging. Achieving an overall accuracy of 86.72%, the model effectively detects early-stage active oak wilt by analyzing color changes in oak tree canopies. Further performance improvements were achieved by integrating Reinforcement Learning from Human Feedback (RLHF), enabling the system to adapt based on user inputs.

The model is deployed through a web platform developed with VueJS and Flask, enhancing accessibility and scalability. By enabling early detection through aerial image analysis, this approach minimizes reliance on manual surveys and contributes to proactive forest conservation efforts.

Keywords: Oak Wilt, Machine Learning, UAV, Convolutional Neural Network, Computer Vision, Forest Health, Image Analysis, Reinforcement Learning from Human Feedback.

1 Introduction

The fungal pathogen *Bretziella fagacearum* causes the destructive vascular disease known as oak wilt, which primarily affects oak trees in North America [16]. This highly transmissible disease spreads through root grafts and sap-feeding beetles that carry fungal spores to healthy trees. Depending on the species, oak trees typically live for 100 to 300 years [14]. However, once infected, they often succumb within weeks, leading to significant ecological and economic losses. Pedler et al. [18] emphasized the potential for oak wilt to spread northward due to climate change, underscoring the urgency of early detection to mitigate its impact. Annual outbreaks result in the loss of thousands of trees across forests and urban landscapes [22], highlighting the critical need for proactive disease management strategies.

Early detection of oak wilt is crucial for effective disease control and timely implementation of measures to prevent its spread [15]. Traditional detection methods, such as manual inspections and field surveys, are resource-intensive and slow, often identifying infections only after visible symptoms have emerged [8]. The inherent delay in these approaches hampers timely intervention and facilitates the uncontrolled propagation of the disease. Emerging technologies, particularly unmanned aerial vehicles (UAVs) and machine learning (ML), present transformative opportunities for forest health monitoring. UAVs can capture high-resolution imagery over large areas [6], while convolutional neural networks (CNNs) have shown exceptional performance in image-based classification tasks [23]. For instance, CNNs can analyze datasets of visible changes in plants to detect diseases, provided that sufficient training data are available [4].

Luo et al. [13] demonstrated the efficacy of hyperspectral imaging combined with convolutional neural networks for vegetation health classification. Similarly, Bismoy et al. [3] developed a deep learning system to translate Bangladeshi and American Sign Languages into written text using CNNs. Although focused on sign language translation, their work underscores the versatility of CNNs for image-based classification, which aligns with the technical methodology employed in this research for detecting oak wilt from aerial imagery. However, these approaches often depend on expensive, specialized equipment, which limits their scalability in practical applications. In contrast, RGB imagery captured by UAVs offers a cost-effective alternative for large-scale monitoring [2]. Studies like Horneo et al. [10] have validated the effectiveness of machine learning models for disease detection, while Stiennon et al. [20] showcased the integration of reinforcement learning from human feedback (RLHF) to iteratively enhance model performance.

In contrast to the work by Ecke et al. [7], which emphasized the integration of UAVs and CNNs for general applications, this research specifically targets oak wilt and proposes an automated early detection system utilizing CNN-based classification with RGB imagery captured by UAVs. The proposed system integrates reinforcement learning from human feedback (RLHF) to enable real-time adaptation and continuous improvement. By employing a lightweight CNN architecture optimized for computational efficiency, the system achieves an accuracy of 86.72% and a positive recall of 78.79%, effectively balancing high accuracy with scalability. Additionally, the system incorporates field feedback to enhance flexibility in dynamic environments. By leveraging geotagged datasets, it enables tracking the spatial spread of oak wilt, thereby supporting conservation efforts through data-driven decision-making.

2 Related Works

Numerous studies have investigated the integration of advanced imaging and machine learning techniques for early disease detection in tree leaf diseases. For example, Sapes et al. [19] employed canopy spectral reflectance to detect oak wilt infections, utilizing high-resolution spectral signatures collected through field-based sensors. Although effective for localized detection, their method lacks scalability due to its dependence on ground-based sensors. In contrast, this research addresses these limitations by leveraging unmanned aerial vehicles (UAVs) to cover larger areas and incorporating CNN-based classification to enhance detection accuracy.

Luo et al. [13] demonstrated the potential of convolutional neural networks (CNNs) for hyperspectral image (HSI) classification in tree health monitoring. By integrating spatial and spectral data, their HSI-CNN framework outperformed other methods, achieving high classification accuracy on benchmark datasets such as Kennedy Space Center and Indian Pines. However, the use of hyperspectral data significantly increases cost and complexity. In contrast, this research mitigates these challenges by utilizing RGB imagery captured by UAVs, offering a cost-effective and scalable solution for disease detection.

Falaschetti et al. [9] developed a low-cost, real-time CNN-based system for plant disease detection using the OpenMV Cam H7 Plus embedded system. Their model achieved high accuracy with minimal computational requirements, showcasing the feasibility of deploying CNNs on resource-constrained hardware. This research aligns with their work by prioritizing a lightweight CNN architecture designed for real-time processing without relying on GPU resources.

Ishengoma and Lyimo [11] addressed the challenges of small datasets and extended training times by combining CNN feature extraction with Random Forest (RF) classifiers. Their ensemble approach demonstrated robustness in the detection of grape leaf disease, achieving a 5.6% improvement in classification accuracy. Their research demonstrates the usefulness of ensemble methods for small datasets, mirroring the use of augmentation techniques in this study to address dataset limitations.

Stiennon et al. [20] integrated Reinforcement Learning from Human Feedback (RLHF) with CNNs to refine model predictions based on human-provided labels, achieving superior performance over conventional metrics. Their feedback-driven optimization seamlessly interacts with this iterative retraining process, enabling the model to continuously improve and adapt to real-world scenarios.

While Uemori et al. [21] applied 3D CNNs for human skin identification using multispectral imagery, their focus on spectral-spatial feature extraction provides valuable insights into feature learning for disease detection tasks. However, our study goes further than multispectral reliance, though, by adding geotagging and RLHF to make the models more flexible in changing environments.

3 Dataset Collection

Fig. 1. Dataset containing high-resolution aerial imagery of oak wilt cases.

This study significantly depends on the dataset to train and enhance the machine learning model for precise oak wilt detection. The data collection process involved multiple phases to ensure diversity and quality. The initial dataset [19] comprises high-resolution aerial images and is used in the early stages of model development, featuring 310 images of forests, roads, houses, and dead trees, alongside 271 images of confirmed oak wilt cases. The dataset presents a highly diversified image in (Fig. 1) depicting dead oak trees (grey) alongside oak trees affected by oak wilt (yellow-orange) in its early stages, illustrating the ecological damage inflicted by oak wilt.

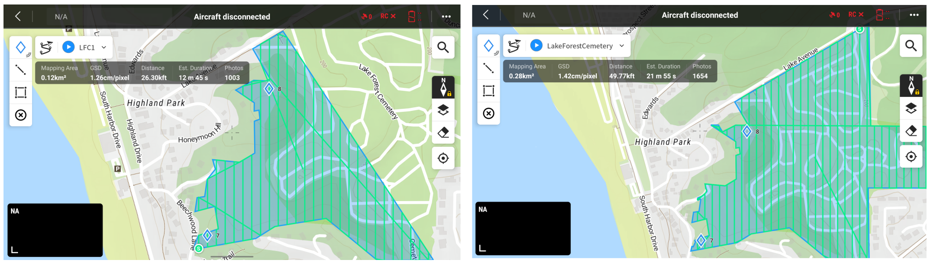

Fig. 2. Flight plan for data collection in Lake Forest Cemetery State Park.

The initial dataset is from Minnesota and has been collected in 2022, necessitating the creation of a dataset from Michigan to obtain updated data and assess any variations in the color of canopies in Michigan during the early stages of oak wilt. As a result, a UAV flight has been flown over several state parks in Grand Haven, a city in West Michigan, during the summer of 2024, targeting areas such as Mulligan's Hollow State Park and Lake Forest Cemetery State Park. The UAV, equipped with multispectral sensors, collected RGB images at a resolution of 5280x3956 pixels while flying at altitudes between 70 and 100 meters. Early in April 2024, the first flight yielded 357 images, despite the absence of visible oak wilt symptoms on the trees. Later flights in May, June, and August significantly increased the dataset with multiple flight plans (Fig. 2), with improved tree development. In total, 1, 646 images have been captured from Lake Forest Cemetery State Park and 1, 598 from Mulligan's Hollow State Park in May, with additional collections made in June and August.

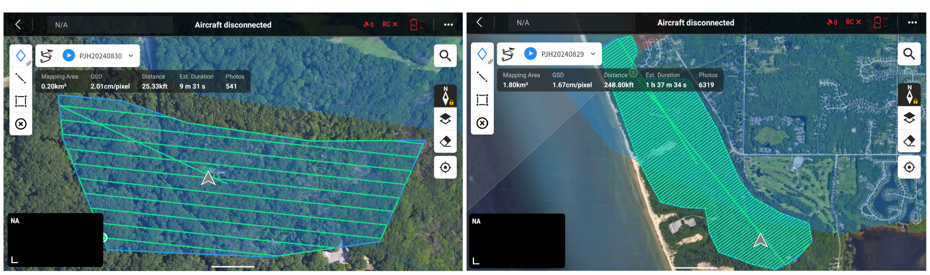

Fig. 3. P.J. Hoffmaster State Park provides a flight plan for both parallel and horizontal flights.

The most comprehensive data has been collected on 30 August 2024, where 1, 120 images from Lake Forest Cemetery State Park and 2, 940 from Mulligan's

Hollow State Park are obtained by horizontal and parallel flight plans (Fig. 3). The selected flying paths ensure that both horizontal and parallel routes are utilized to fully cover all locations, capturing images of even the smallest regions and leaving no trees unphotographed. However, active oak wilt cases remained absent. To address this, data collection has been extended to Warren Dunes State Park and P.J. Hoffmaster State Park, with 2,100 images captured in Warren Dunes State Park, including 36 crucial images of active oak wilt infections (Fig. 4).

Fig. 4. Data collection at Warren Dunes State Park highlighting active oak wilt infections.

4 Methodology

4.1 Dataset Selection

The construction of a robust dataset is foundational to the development of an accurate machine learning model. This study utilizes an initial dataset [19] from Minnesota, containing 271 images of oak wilt-infected trees and 310 images of unrelated objects such as roads, fields, and non-forest areas. This dataset provides foundational variability, enabling the model to differentiate diseased trees from irrelevant environmental features.

To enhance the model's generalization capabilities, additional images were collected during the summer of 2024 (Fig. 5). UAV flights were conducted across key sites, including Lake Forest Cemetery State Park, Mulligan's Hollow State Park, P.J. Hoffmaster State Park, and Warren Dunes State Park, resulting in a comprehensive dataset comprising 9, 981 images. This includes 36 unique images of active oak wilt infections. As a result, 271 and 36, total 307 unique images have been labeled as "Oak Wilt." Labeling has been carried out by inter-rater agreement between 4 persons; 2 of them are forest and oak wilt experts from the Michigan Department of Natural Resources [5]. Within the collected dataset, to maintain diversity and maintain a proper ratio between "Oak Wilt" and "Not Oak Wilt" classes, 678 images from the entire dataset have been labeled as "Not Oak Wilt." This classification contains roads, green trees, dead trees, cemetery, houses, fields, grass, etc. UAVs with 4K imaging and multispectral sensors collect the datasets with high resolution consistency, ensuring consistent training and testing procedures. To address the inherent imbalance of oak wilt data, augmentation techniques such as rotations, flips, and shearing were applied, generating diverse training samples. The resulting dataset contained 373 augmented oak wilt images and 678 balanced environmental images, forming the basis for model training and testing.

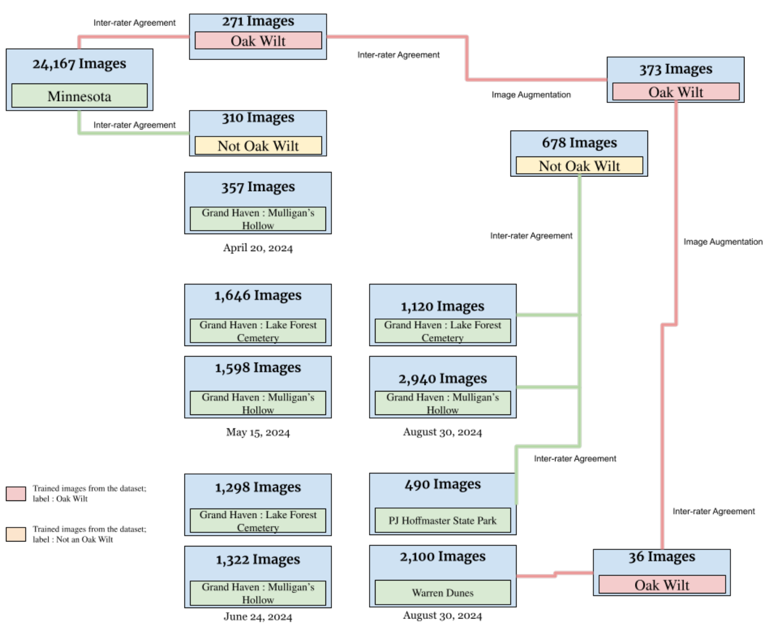

Fig. 5. Dataset selection and expansion during Summer 2024

4.2 Data Preprocessing

Efficient preprocessing has been implemented to standardize UAV-captured images, ensuring optimal model training and testing performance. Each image is resized to 256×256 pixels, maintaining consistency in input dimensions and compatibility with the CNN architecture. Pixel intensity values were normalized to a $[0, 1]$ range to prevent gradient saturation and expedite model convergence [12]. Emphasizing the lightweight implementation of the system, the dataset's color has been set to RGB during preprocessing rather than utilizing multispectral photos, as the canopy of oak trees exhibits color changes during the early stages of oak wilt, which can be distinctly identified in a 4K aerial image recorded from a height of only 70-100 meters above the subject.

The dataset has been split into training (70%), validation (20%), and testing (10%) subsets, ensuring balanced representation of both classes. Augmentation strategies were applied using TensorFlow's `ImageDataGenerator`, enabling real-time transformations and enhancing model robustness against overfitting. Due to a limited dataset of unique 'Oak Wilt' images, image augmentation is conducted solely on the 'Oak Wilt' images captured in Michigan in 2024, together with selected significant images from the initial dataset, to augment and enrich the diversity of the 'Oak Wilt' dataset. Augmentation not only improved variability but also simulated real-world conditions such as diverse lighting and viewing angles. Additionally, geotagging leveraging GPS data embedded within UAV images has been incorporated. This simplified the mapping of predictions to specific locations and demonstrated the prevalence of oak wilt, thereby expanding the model's potential beyond simple classification.

4.3 Model Architecture and Training

The core architecture is a Convolutional Neural Network (CNN), chosen for its exceptional performance in image-based tasks [23]. The network consists of three convolutional layers, each employing 3×3 kernels for feature extraction. After each convolutional layer, max-pooling layers are added to reduce the number of spatial dimensions while keeping important features and lowering the risk of overfitting. Dropout layers were included, which randomly deactivate neurons during training, ensuring improved generalization. The output layer utilizes a softmax activation function for probabilistic predictions in binary classification tasks.

Training utilized the Adam optimizer with binary cross-entropy as the loss function, defined as:

$$L = -\frac{1}{N} \sum_{i=1}^{N} \left[y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i) \right],$$

where y_i is the true label and $\hat{y}_i$ is the predicted probability. The model has been trained over 100 epochs, with notable convergence observed after approximately 20 epochs. This rapid convergence highlights the model's ability to efficiently learn from the diverse and augmented dataset (Fig. 6).

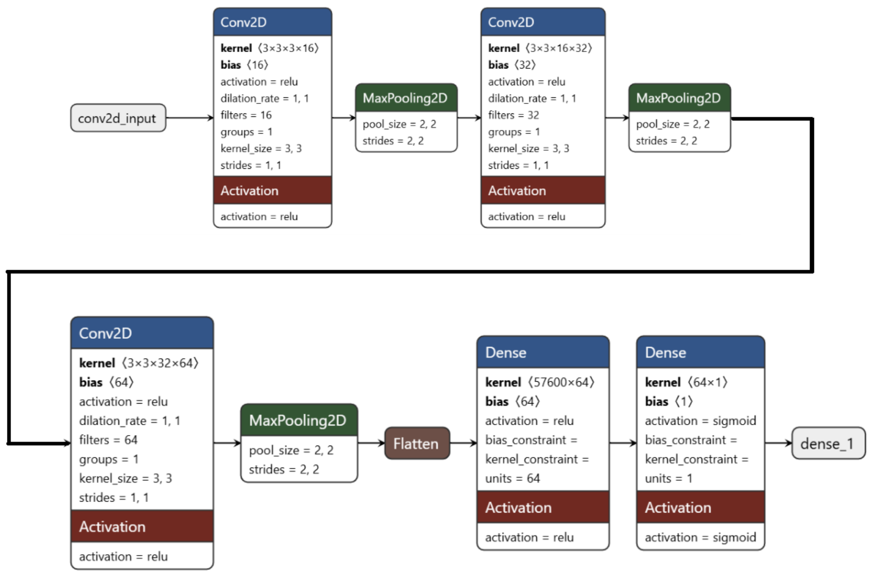

Fig. 6. Convolutional layers in the CNN architecture

4.4 Reinforcement Learning from Human Feedback (RLHF)

Reinforcement Learning from Human Feedback (RLHF) has been integrated into the system to iteratively refine model performance based on real-world user corrections [1]. Users upload UAV-captured images for classification, with the model assigning labels such as "Healthy," "Oak Wilt," or "Dead Trees." The model flags misclassified samples and stores user-provided corrections in a database for retraining.

RLHF updates the model parameters θ using gradient adjustments:

$$\theta_{t+1} = \theta_t - \alpha \nabla_\theta L(x^{(i)}, y^{(i)}),$$

where α represents the learning rate, $x^{(i)}$ the input sample, and $y^{(i)}$ the corrected label. Over successive iterations, RLHF minimizes errors, adapting the model to evolving real-world scenarios. Figure 7 demonstrates how iterative RLHF significantly enhanced model performance, particularly in challenging edge cases.

4.5 Web Application Deployment

A user-friendly web application has been developed to facilitate interaction with the oak wilt detection system. Built with VueJS for the frontend and Flask for the backend, the application enables seamless image uploads, real-time classification, and feedback submission. VueJS provides a dynamic interface with responsive features, while Flask ensures robust backend operations, including TensorFlow-based model inference and database management. The web application allows

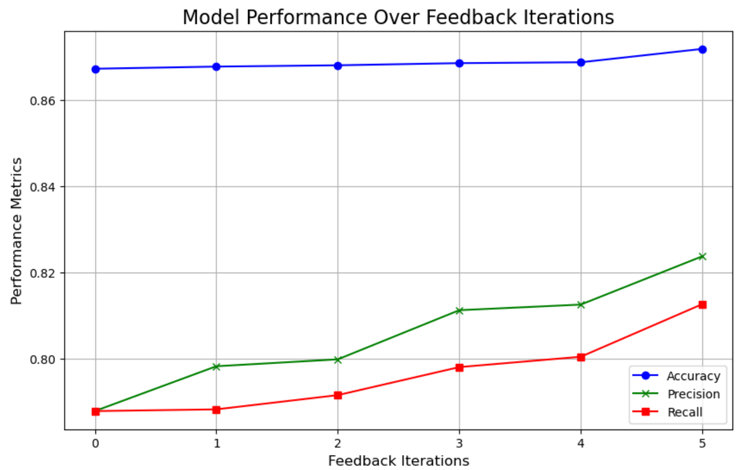

Fig. 7. Improvement in model performance through RLHF iterations

users to upload an unlimited number of images, and the system predicts whether any images exhibit early signs of oak wilt or dead oak trees. The user will also be able to ascertain the precise location of the tree, achieved through the integration of 'OpenStreetMap' [17]. The user has the opportunity to visit the place in person to address the oak wilt. If the system makes an erroneous prediction, the user can submit input, which will enable the system to enhance its performance in the future.

The application processes each image with an average inference time of 121.94 milliseconds, emphasizing real-time efficiency. Export functionalities in CSV and GeoJSON formats further extend its utility, enabling comprehensive geospatial analysis for forest management. The system, illustrated in Fig. 8, ensures scalability and adaptability, making it well-suited for large-scale deployment.

This platform, which integrates RLHF and real-time classification, serves as a bridge between advanced machine learning techniques and practical field applications. It empowers users with actionable insights, ensuring proactive forest conservation.

5 Results and Discussions

Using UAV-taken aerial pictures, the proposed convolutional neural network (CNN) model showed promise in finding oak wilt infections in their early stages. The dataset, which included 373 "Oak Wilt" and 678 "Not Oak Wilt" images, presented a balanced binary classification problem. After training the model for 100 epochs with a 70%-20%-10% train-test-validation split, the model achieved an accuracy of **86.72%**, indicating its effectiveness in generalizing across unseen data.

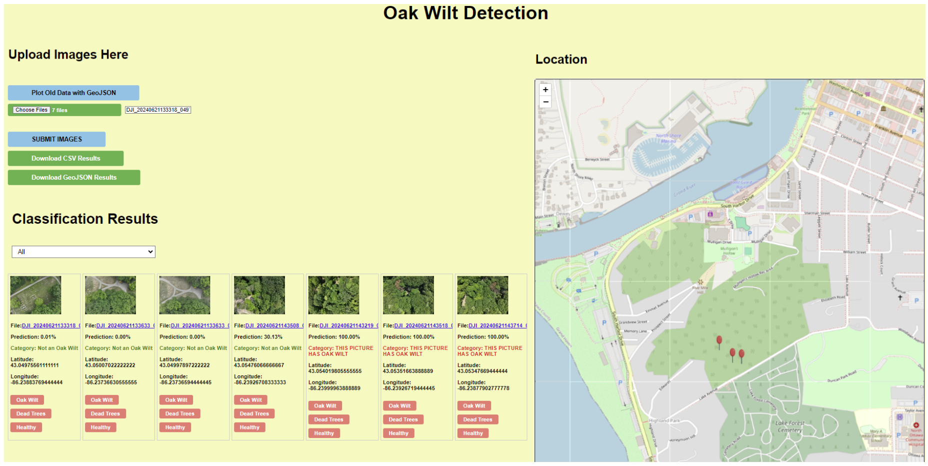

Fig. 8. Web application for oak wilt detection and feedback collection

5.1 Precision, Recall, and F1-Score

Precision, which measures the ratio of correctly predicted positive instances, has been calculated for the "Oak Wilt" class as:

$$\text{Precision} = \frac{TP}{TP + FP}$$

where TP and FP represent true positives and false positives, respectively. The precision of oak wilt is 78.79%, while healthy trees achieved 90%, yielding a weighted average of **86.72%**.

Recall quantifies the sensitivity of the model in detecting true positives:

$$\text{Recall} = \frac{TP}{TP + FN}$$

where FN represents false negatives. The recall for oak wilt is 79.79%, reflecting the model's capability to detect positive cases effectively. The weighted average recall is **87%**.

The F1-score, defined as the harmonic mean of precision and recall, is calculated as:

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

and recorded a balanced value of **79.79%**, indicating an equilibrium between precision and recall.

5.2 Class-Specific Recall

Breaking down recall by class, the model exhibited strong performance for healthy trees (label 0) with a recall of 90%:

$$\text{Recall}_{\text{Healthy}} = \frac{TP_{\text{Healthy}}}{TP_{\text{Healthy}} + FN_{\text{Healthy}}}.$$

However, for oak wilt (label 1), the recall is 79.79% (Fig. 9), reflecting the challenges in detecting subtle symptoms of early-stage infections. Factors such as the sparse data for infected trees and the variability in aerial imagery contributed to these results.

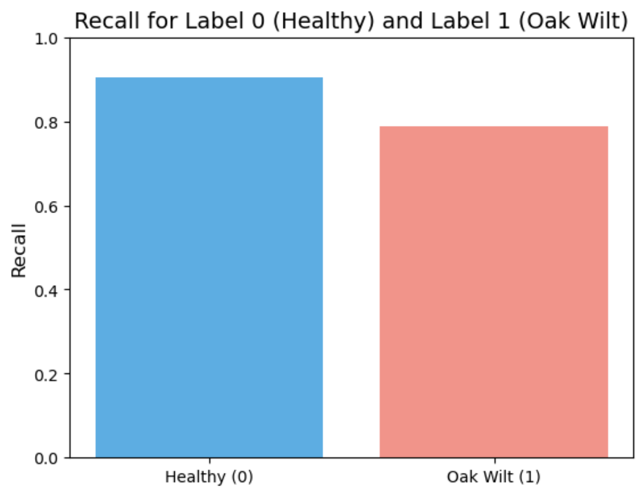

Fig. 9. Class-Specific Recall

5.3 Confusion Matrix and Error Analysis

The confusion matrix (Fig. 10) provides a detailed breakdown of the model predictions, capturing true positives, true negatives, false positives, and false negatives. For the "Oak Wilt" class, the model correctly classified 52 instances but misclassified 14 as healthy trees. Similarly, 131 healthy trees were correctly identified, with 14 misclassified as oak wilt.

These incorrect classifications highlight the need for improved feature differentiation, particularly in addressing false negatives, which pose significant risks in real-world scenarios. Improving the model to handle such cases is crucial for mitigating the spread of oak wilt.

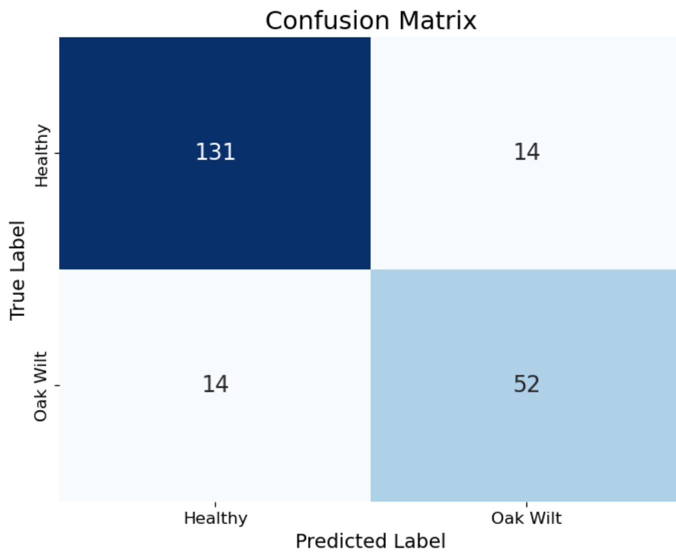

Fig. 10. Confusion Matrix of Model Predictions

5.4 Model Training and Convergence

The model exhibited rapid convergence, stabilizing after approximately 20 epochs. The training and validation accuracy curves (Fig. 11) show a consistent improvement, with the final validation accuracy reaching 86.72%. The training process employed the binary cross-entropy loss function:

$$L = -\frac{1}{N}\sum_{i=1}^{N}\left[y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)\right],$$

where y_i is the true label and $\hat{y}_i$ is the predicted probability. The gradual decrease in loss further validated the robustness of the training process.

5.5 Inference Time and Ablation Study

The model's average inference time is 121.94 ms per image (Fig. 12), demonstrating its practicality for real-time field applications. An ablation study revealed that simpler architectures, while computationally efficient, suffered from accuracy drops. Advanced architectures like Vision Transformers (ViT) improved accuracy but required higher computational resources, making them unsuitable for this study's goals.

The chosen architecture balances computational efficiency and performance, achieving the accuracy of 86.72%. This lightweight model is ideal for large-scale deployment, requiring minimal hardware resources while maintaining competitive performance metrics.

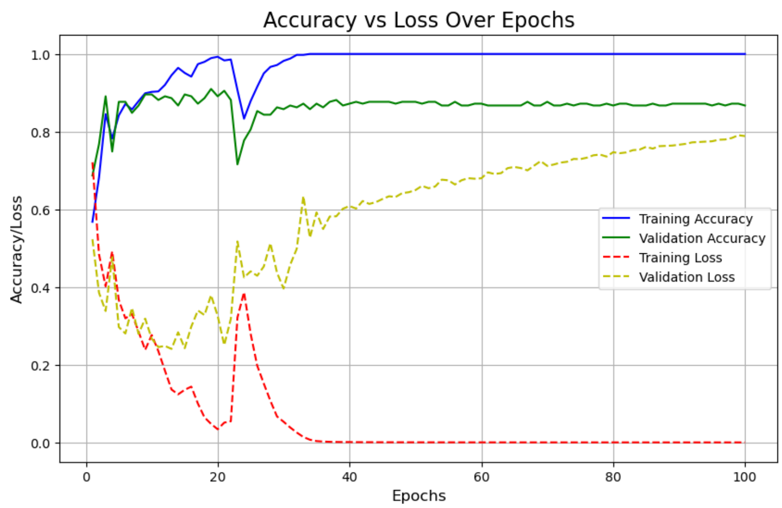

Fig. 11. Training and Validation Accuracy vs. Loss

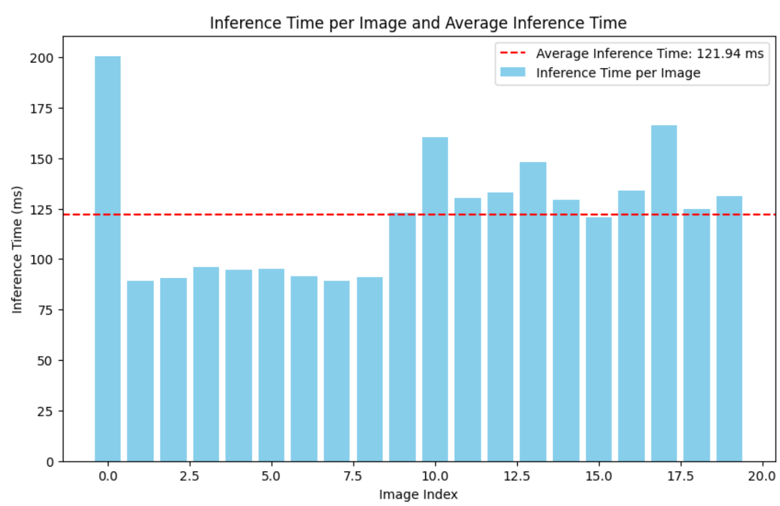

Fig. 12. Inference Time per Image

5.6 Future Directions

Future work will explore ensemble models and transfer learning to improve performance further. Adding more diverse datasets and more advanced preprocessing techniques could also help fix the problems that are already there, especially when it comes to finding oak wilt infections early on.

6 Conclusion

This study developed an automated system for the early detection of oak wilt by applying convolutional neural networks (CNN) to aerial images captured by UAVs. With a dataset of 1,051 RGB images from several state parks in Michigan, the model achieved an accuracy of **86.72%**, with balanced precision and recall scores of **78.79%**, demonstrating its usefulness in large-scale forest monitoring in real time. Using UAV technology, the system offers a scalable approach to capturing high-resolution images of oak trees, allowing early intervention to mitigate the spread of oak wilt. One of the key strengths of this approach is the simplicity and efficiency of the model. Despite utilizing only CPU resources, it effectively processes high-resolution images with real-time inference capabilities, making it well-suited for field applications where GPU resources may be limited. The lightweight architecture allows for faster inference times, lower power consumption, and scalability, which are critical in real-world scenarios involving large datasets and remote fieldwork. The implementation of Reinforcement Learning from Human Feedback (RLHF) also improved its future usability and the chances of improvements. While the model performed well in identifying healthy and infected trees, slight limitations in recall for oak wilt suggest the need for further optimization, particularly in addressing false negatives. In general, this research highlights the feasibility of integrating machine learning and UAV technology for effective forest disease management and environmental conservation.

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