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RESEARCH ARTICLE
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Enhancing Agricultural Productivity and Innovation: Deep Learning for Citrus Disease Classification in Thai Orchards

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ABSTRACT

Citrus diseases present significant challenges to global agricultural productivity and economic stability, with pathogens such as bacteria, fungi, viruses, and phytoplasmas causing severe crop losses. Among these, thrips, California red scale, and sooty mold are particularly destructive, highlighting the need for early detection and precise identification to manage these threats effectively. This article proposes a machine vision and deep learning approach for rapidly classifying citrus diseases. A dataset comprising 900 images of three different citrus diseases was captured from Sai Nam Phueng orange orchards in Chiang Mai Province, Thailand, and separated into training and validation sets at a ratio of 80:20. Convolutional Neural Networks (CNNs) were constructed using MobileNetV2 for pre-training and achieved 97.22% accuracy in disease classification, demonstrating its potential to enhance disease prediction and prevention within the citrus industry. The model's performance was assessed through confusion matrices, revealing robust classification results consistent with existing studies.

Keywords: Citrus diseases, Deep learning, Convolutional Neural Networks, MobileNetV2, Agricultural disease management

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INTRODUCTION

Citrus fruits hold substantial commercial significance in Thailand due to their significant capacity to generate income for farmers. Among the varieties cultivated, tangerines are especially prominent, with the northern region accounting for the largest planted area (Somsri & Vichitrananda, 2007; Maciel et al., 2023). In 2020, Chiang Mai Province alone boasted an extensive 31,685 rai dedicated to orange cultivation, yielding an impressive 2,820 kg/rai. Notably, the Sai Nam Phueng variety is another popular type of orange extensively cultivated by farmers in the Fang District of Chiang Mai Province. This variety is favored for its juicy, flavorful flesh, appealing yellow skin, and high consumer demand. To consistently produce high-quality oranges with desirable taste and quality, several critical factors must be considered, including soil nutrient levels and climatic conditions. However, rising production costs, particularly those related to chemical fertilizers, have significantly increased the financial burden on farmers. Additionally, fluctuating weather patterns have exacerbated the occurrence of various diseases in orange plantations (Dala-Paula et al., 2019; Taylor et al., 2019; Pathak et al., 2021). As a result, the quality of the produce often suffers, leading to inconsistencies in sweetness and appearance, ultimately diminishing its market value.

Citrus diseases have a considerable impact on the quantity and quality of citrus fruits worldwide, severely affecting agricultural output and economic stability (Sun et al., 2019; Urbaneja et al., 2020; Dhiman et al., 2022; Naqvi et al., 2022). These diseases, attributed to a diverse array of pathogens, including bacteria, fungi, viruses, and phytoplasmas, are responsible for severe economic losses

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in the citrus industry. Among these, Huanglongbing (HLB), also known as citrus greening, is one of the most destructive diseases. It is caused by the bacterium *Candidatus Liberibacter* asiaticus and is primarily spread by the Asian citrus psyllid (*Diaphorina citri*) (Li et al., 2021). HLB inflicts extensive damage on the plant's vascular system, leading to symptoms such as leaf chlorosis, stunted growth and ultimately, tree mortality (Dala-Paula et al., 2019). Another critical disease affecting citrus crops is citrus canker, caused by the bacterium *Xanthomonas axonopodis* pv. citri, manifesting as lesions on leaves, stems, and fruits, resulting in premature fruit drops and decreased marketability of the produce. Additionally, Phytophthora Root Rot and Gummosis, caused by *Phytophthora* species, target the root system and trunk, compromising nutrient uptake and weakening the tree's structural integrity (Van den Berg et al., 2021; Bouqellah et al., 2024). Early detection and correct identification of these citrus diseases are critical to mitigating their impact. Traditionally, plant diseases are diagnosed in agricultural laboratories using specialized procedures to detect specific pathogens (Utpal et al., 2020; Zhang et al., 2020; Buja et al., 2021). In some cases, plant pathologists support farmers in diagnosing problems based on visual indications. However, while this procedure is useful, it is primarily dependent on the pathologist's skill and may not always produce accurate or timely results, especially in the early stages of illness onset. Consequently, to improve the efficiency of citrus disease management, methods for identifying citrus leaf diseases must be developed and implemented in a fast, intelligent, and effective manner.

Deep learning has emerged as a useful tool across a range of fields, including agriculture, where it is increasingly used to identify and classify plant diseases (Appalanaidu & Kumaravelan, 2021; Li et al., 2021; Wang et al., 2022; Jafar et al., 2024). Among the various deep learning techniques, convolutional neural networks (CNNs) have been recognized as being particularly effective for these tasks. Notable CNN architectures, such as MobileNet, have been widely used to detect and classify plant diseases (Saleem et al., 2020; Hassan et al., 2021; Elfatimi et al., 2022). Furthermore, numerous researchers have applied deep learning models to the specific challenge of identifying and classifying citrus diseases. Noteworthy contributions in this area include the work of Rehman et al. (2022), Barman and Ridip (2021), and Xiaoling et al. (2016), who have demonstrated the efficacy of deep learning approaches in enhancing the accuracy and efficiency of citrus disease management. This study aims to utilize CNNs for the accurate identification and classification of citrus diseases, with the goal of supporting early detection and effective management. The findings are expected to provide a foundation for mobile applications that enable real-time disease analysis in the field.

MATERIALS & METHODS

Preparation of Citrus Disease Images

This study used a dataset comprising 900 images of citrus diseases collected from the Sai Nam Phueng orange orchards in Fang District, Chiang Mai Province. The images were captured using an iPhone 13 at a resolution of 3024 × 4032 pixels and saved in JPEG format. The dataset includes three different citrus diseases: thrips, California red scale, and sooty mold (Fig. 1). To aid the development and evaluation of an image classification model designed to distinguish between these citrus disease types, the dataset was divided into training and validation sets at a ratio of 80:20.

A B C

Fig. 1: Images of citrus disease (A) thrips, (B) California red scale, and (C) sooty mold.

Image Preprocessing and Data Augmentation

To mitigate overfitting and enhance the accuracy of CNNs, the availability of extensive training datasets is crucial. Consequently, data augmentation techniques are commonly employed to expand and diversify the dataset (Shorten & Khoshgoftaar, 2019; Mumuni & Mumuni, 2022; Santos & Papa, 2022; Alomar et al., 2023). In this study, the training images were subjected to random rotations, horizontal and vertical flips, and normalization to account for the variability encountered in real-world conditions. These augmented images were then included in the training process alongside the original sample images, thereby improving the model's classification precision and robustness (Fig. 2).

Convolutional Neural Networks

Deep learning, an area of machine learning, has shown significant effectiveness in image classification tasks due to its ability to autonomously extract high-dimensional and abstract features from training samples using neural networks. This study describes a deep learning methodology for classifying citrus diseases that uses CNNs and is implemented using the TensorFlow framework in a Python development environment. The neural network architecture employed in this research is MobileNetV2 for pre-training, chosen for its efficiency and effectiveness in resource-limited settings. This model consists of six layers: five depth-wise separable convolutional layers that minimize the computational cost and a final output layer optimized for precise citrus disease classification. The ReLU serves as the activation function, complemented by 2×2 max pooling. The output from the final layer is processed using the softmax function to generate probability distributions for predicting three distinct types of citrus diseases. The model underwent training across 30 epochs. Fig. 3 provides an in-depth illustration of the CNN architecture used in this study.

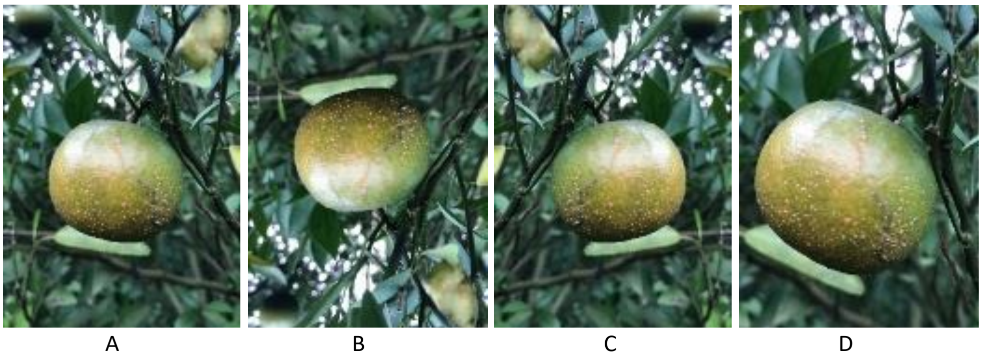

Fig. 2: Data enhancement: (a) Original, (b) Flip vertical, (c) Flip horizontal, and (d) Random rotation.

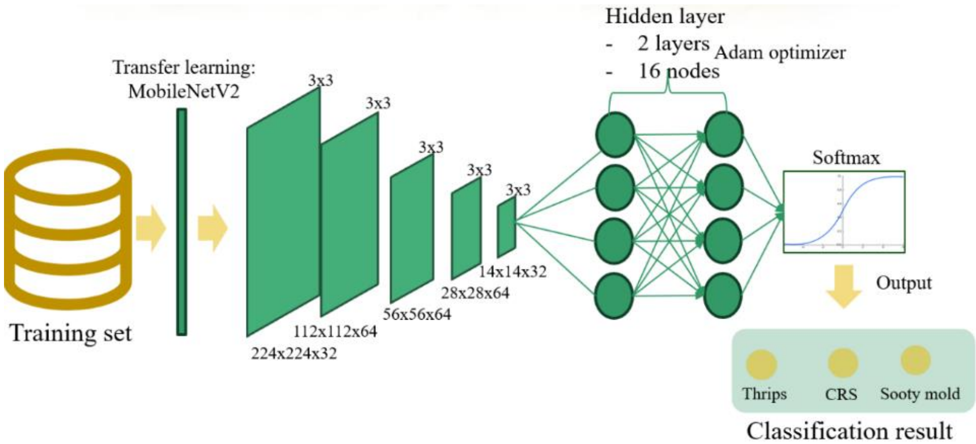

Fig. 3: Process of Convolutional Neural Networks and the classification of citrus disease.

Performance Evaluation

In this study, a confusion matrix was employed to visualize the performance of the CNN model. The confusion matrix compares the samples' actual classes to those predicted by the CNN classifier, capturing four primary metrics: true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). Specifically, TP and TN indicate correct citrus disease identification, whereas FP and FN indicate incorrect classification (Monaghan et al., 2021; Chicco & Jurman, 2023). The model's performance was assessed using several statistical measures derived from the confusion matrix: accuracy, precision, sensitivity, and F1-score. These metrics were calculated using images from the test set, accompanied by labels not utilized during training. The performance evaluation formulas are presented in Table 1.

Table 1: Performance evaluation to measure the performance of the CNN model

Metrics	Formula	Evaluation Focus
Accuracy	$\frac{TP+TN}{TP+FP+FN+TN}$	The sum of correct predictions is divided by the total number of predictions.
Precision	$\frac{TP}{TP+FP}$	The high score indicates low false positives, resulting in higher classification.
Sensitivity	$\frac{TP}{TP+FN}$	This represents the ability of the model to identify instances of specific classes.
F1-score	$\frac{2\times precision\times sensitivity}{precision+sensitivity}$	Its high score indicates that the model classifies accurately.

RESULTS & Discussion

The performance of the model was evaluated by monitoring the accuracy and loss metrics across training epochs. Fig. 4 presents the trends in accuracy and loss for both the training and validation datasets over the course of training. During the initial phase, spanning epochs 1 to 10, there was a notable decrease in loss values, coinciding with a significant improvement in accuracy. These observations indicate effective learning during the early training stages. By the end of the training process, the CNN models demonstrated a high level of performance, achieving training accuracy exceeding 92% (0.92) and maintaining loss values consistently below 0.15. These results underscore the model's robustness and reliability in learning from the data (Allal et al., 2024; Lin, 2024). Furthermore, the models exhibited convergence by approximately the 15 epoch, suggesting that the training process was efficient and reached stability within a relatively short time frame. Such performance highlights the efficacy of the chosen architecture and optimization strategy in facilitating rapid and reliable convergence to optimal solutions.

After completing the training phase, the model's performance was systematically evaluated using a confusion matrix, providing a detailed breakdown of classification outcomes based on true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). This approach allows for a comprehensive understanding of the model's accuracy and potential areas of misclassification. Fig. 5 presents two versions of the confusion matrix: an unnormalized matrix and a normalized matrix.

In the unnormalized confusion matrix, 57 images of thrips were correctly classified as belonging to the thrip category, demonstrating the model's ability to accurately identify the majority of instances. However, minor misclassifications were observed: two thrip images were incorrectly identified as belonging to the California red

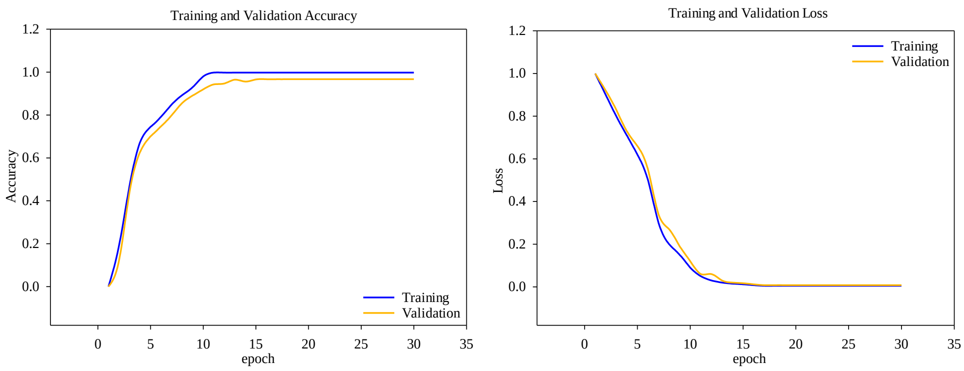

Fig. 4: Training and validation accuracy, along with training and validation loss.

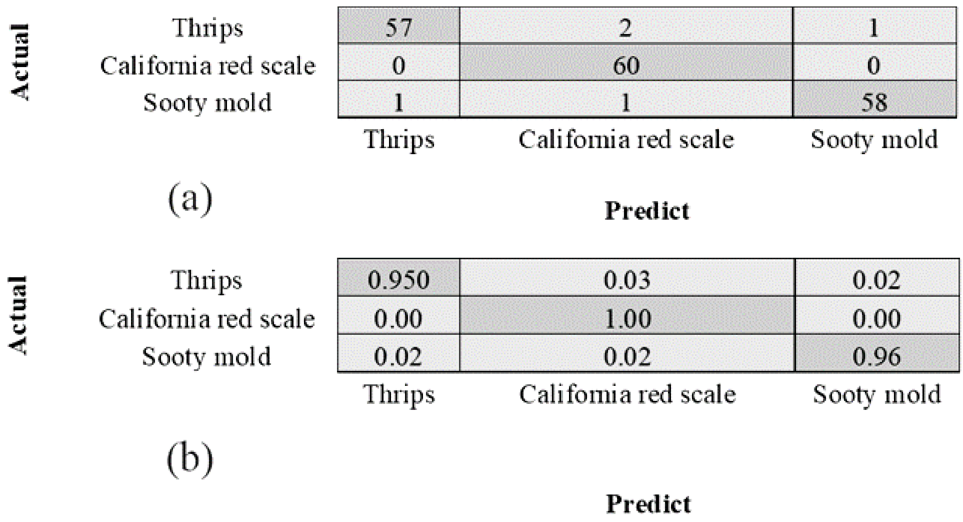

Fig. 5: Confusion Matrix (a) without normalization and)b (with normalization.

scale category and one thrip image was misclassified as sooty mold. For the California red scale category, the model achieved flawless classification, with all 60 images being accurately identified as the California red scale. Similarly, for the sooty mold category, there were minor misclassifications: one image was incorrectly classified as thrips and another was mistakenly labeled California red scale.

The normalized confusion matrix provides an additional layer of insight by expressing the classification outcomes as proportions or percentages of the total predictions. This normalization facilitates easier comparison across categories with varying sample sizes. As illustrated, the model achieved a 95% correct classification rate for the thrip category, a perfect 100% classification accuracy for the California red scale, and a 96% correct classification rate for sooty mold. These results highlight the model's high level of accuracy and its ability to generalize across diverse categories.

To further quantify the model's performance, several evaluation metrics derived from the confusion matrix are presented in Table 2. These include accuracy, precision, sensitivity (also known as recall), and F1-score. Accuracy measures the overall proportion of correct predictions out of all the predictions made by the model. Precision assesses the proportion of true positive predictions relative to all positive predictions, reflecting the model's ability to avoid false positives. Sensitivity evaluates the proportion of true positives relative to the actual number of positive instances, providing insight into the model's capability to detect true cases without missing any. Lastly, the F1-score, the harmonic mean of precision and sensitivity, serves as a balanced metric that considers both false positives and false negatives.

Table 2: Classification results for the CNN model

Accuracy (%)	Precision (%)	Sensitivity (%)	F1-Score (%)
97.22	97.27	97.22	97.22

The mean values for these metrics, as displayed in Table 2, further reinforce the model's robust classification capabilities. The high mean accuracy suggests that the model reliably identifies most instances correctly, while the strong precision and sensitivity values indicate it performs well in both identifying true positives and minimizing false positives and negatives. The F1-score, being consistently high, confirms that the model achieves a balanced performance across all categories.

Overall, the results from the confusion matrix and the associated performance metrics demonstrate the efficacy of the model in accurately classifying the given categories. The minimal misclassification rates, particularly in the thrip and sooty mold categories, indicate areas for potential refinement but do not detract significantly from the model's overall performance. The perfect classification of the California red scale category highlights the strength of the model in handling certain categories with absolute precision. These findings underscore the utility of the developed model for practical applications, where accurate and reliable classification is essential.

Future improvements could focus on addressing the misclassifications observed in the thrip and sooty mold categories. This may involve enhancing the feature extraction process or incorporating additional training data to improve the model's discriminative power. Moreover, further analysis of the misclassified instances could provide valuable insights into specific patterns or characteristics that might have led to errors. Such refinements would not only enhance the model's overall accuracy but also contribute to its robustness in real-world scenarios where diverse and challenging datasets are often encountered.

The findings of this study align closely with prior research, notably those conducted by Gandhi et al. (2018) and Picon et al. (2019), who utilized MobileNet CNN to detect banana and tomato diseases. Their respective models achieved high accuracies of 92% and 96%, underscoring the robustness of MobileNet architectures in plant disease detection. Additionally, previous studies have explored the use of MobileNet CNNs specifically for citrus disease classification. For instance, Xing et al. (2019) employed MobileNetV1 and MobileNetV2 to classify seven types of citrus diseases, achieving testing accuracies of 85.04% and 87.82%, respectively. When compared to the current research, the classification accuracy reported in this study exceeds that of Xing et al. (2019), demonstrating a performance improvement in the detection of citrus diseases.

The present study also surpasses the results of Utpal et al. (2020), who employed MobileNetV2 to classify three types of citrus diseases, reporting a classification accuracy of 92%. This comparison further emphasizes the advancements made in the current work. Beyond MobileNet CNN, other CNN architectures have been applied to citrus disease classification with similarly competitive outcomes. For example, Yadav et al. (2024) utilized the VGG16 architecture, combined with hyperspectral imaging, to classify Citrus Black Spot (CBS) and citrus canker diseases. This approach yielded an overall accuracy of 93%, showcasing the potential of integrating advanced imaging techniques with CNN models for enhanced disease classification.

Moreover, Jasim et al. (2020) developed a CNN model tailored to classify seven distinct classes of citrus diseases: anthracnose, brown rot, CBS, citrus canker, citrus scab, melanose and sooty mold. Their model achieved an overall accuracy of 88%, which, while significant, is lower than the results reported in the current research. These findings illustrate the continuous evolution and refinement of CNN-based methodologies in agricultural applications.

Vinay and Poonam (2020) explored the classification of oranges into two categories: "good" and "damaged" using a dense CNN architecture. They tested two distinct preprocessing strategies: one without image preprocessing and augmentation, resulting in a classification accuracy of 67%, and another with preprocessing and augmentation, achieving a substantially improved accuracy of 89.1%. These results highlight the critical role of preprocessing and data augmentation techniques in enhancing CNN performance, particularly in scenarios involving complex or imbalanced datasets.

Collectively, this study and the aforementioned research highlight the efficacy of CNN-based models in the classification of citrus diseases. The ability of CNNs to learn intricate patterns from visual data, such as symptoms of plant diseases, makes them invaluable tools in precision agriculture. The higher classification accuracies observed in this study compared to earlier works underscore the impact of architectural improvements, optimized hyperparameter configurations, and potentially larger or more diverse datasets.

Future research could build upon these findings by integrating complementary techniques, such as hyperspectral imaging, transfer learning, or ensemble modeling, to further enhance the robustness and generalizability of citrus disease classification systems. Additionally, expanding the scope of the study to include real-time detection capabilities in field conditions would be a valuable direction, ensuring that these models could address the practical challenges faced by farmers and agricultural stakeholders. Ultimately, the collective body of research reaffirms the transformative potential of CNNs in revolutionizing plant disease management, paving the way for more sustainable and efficient agricultural practices.

Conclusion

This study successfully demonstrated the application of deep learning for the classification of citrus diseases prevalent in Thai orchards. The model achieved an accuracy rate of 97.22%, underscoring its potential for improving disease detection and management in the citrus industry. The integration of data augmentation techniques further improved the model's robustness, ensuring its effectiveness in real-world scenarios. These findings are consistent with previous research utilizing CNNs for plant disease identification, affirming the efficacy of deep learning in agricultural applications. The results of this research contribute significantly to the field by offering a practical tool for citrus disease management, which could be further developed into mobile applications for real-time disease analysis by farmers. Future work could explore the expansion of the dataset to include a broader range of diseases and the implementation of more advanced deep learning models to increase classification accuracy.

Conflict of Interest: The authors declare that they have no conflict of interest.

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