Vol. 07, No. 3 (2025) 1781-1790, doi: 10.24874/PES07.03A.005

Proceedings on Engineering Sciences

www.pesjournal.net

METROLOGICAL IMPACT ON ORANGE FRUIT: A COMPARATIVE ANALYSIS OF DEEP LEARNING MODELS FOR PREDICTING FRUIT DISEASES

Lawrence Kujur[1]
Varuna Gupta
Abhinav Singhal

Received 15.01.2025
Revised 06.03.2025
Accepted 12.05.2025

Keywords:

Metrology, Convolutional Neural Networks (CNNs), Gradient Boosting (CNN-GB), Hybrid Models, Measurement Accuracy, Fruit Disease Prediction

A B S T R A C T

This research offers a comprehensive comparative analysis of efficient deep learning models for predicting diseases in orange fruits, with a particular emphasis on the impact of meteorological factors on disease prevalence. Citrus diseases such as Blackspot, Canker, and Greening are significantly influenced by environmental conditions. Recognizing the crucial role of weather conditions in the development and spread of these diseases, we concentrate on enhancing prediction accuracy by integrating Convolutional Neural Networks (CNNs) with various classification algorithms to develop hybrid models that account for meteorological impacts.

Specifically, we assess the performance of a CNN combined with Gradient Boosting (CNN-GB) and compare it against other hybrid models such as CNN integrated with Long Short-Term Memory networks (CNN-LSTM), Support Vector Machines (CNN-SVM), and Random Forest classifiers (CNN-Random Forest). These models are evaluated using different optimization algorithms to determine the most effective approach for disease prediction under varying meteorological conditions.

A meticulously curated dataset comprising 1,600 training images and 300 testing images of orange fruits exhibiting a variety of disease symptoms was utilized for evaluation. The dataset reflects diverse environmental conditions to capture the meteorological impact on disease manifestation. All the models tested, the CNN-GB hybrid model with NDAM optimizer exhibited superior performance (Accuracy 98.03) in comparison of other models like CNN (Accuracy 96.03), CNN+LSTM (Accuracy 96.16), CNN + SVM (Accuracy 97.13) and CNN + Random Forest (Accuracy 97.79).

The exceptional performance of the CNN-GB model suggests that integrating CNNs with powerful classification algorithms like Gradient Boosting, along with considerations of meteorological data, can significantly enhance disease detection in crops. This advancement contributes to more proactive and effective disease management strategies, ultimately reducing economic losses and increasing productivity in the agricultural sector.

[1] Corresponding author: Lawrence Kujur
Email: lawrence.kujur@christuniversity.in

1. INTRODUCTION

The importance of agribusiness to the global economy is huge and fruit farming in particular has an important place too. Especially for businesses, but there are also important nutritional benefits to this large-scale export such as the economic value of oranges. But orange production faces constraints in the form of numerous diseases causing significant yield losses and quality deterioration. Hence, early and accurate diagnosis of these diseases is crucial for their effective control and reducing the economic burdens associated with them.

Recent advances in deep learning allow the development of automated and accurate diagnostic tools, useful for detecting diseases in agriculture. Among these, Convolutional Neural Networks (CNN) have attracted a great deal of attention and achieved state-of-the-art performance in the field of image recognition through feature learning from data. Prior studies have proven the effectiveness of CNNs in recognition of plant diseases. This study underscores the potential of advanced deep learning techniques in agriculture-specific disease prediction, highlighting the importance of incorporating meteorological factors. By effectively predicting disease outbreaks associated with specific weather patterns—such as the higher incidence of Citrus Black Spot during periods of elevated humidity and rainfall—the models provide valuable insights for farmers and agricultural technologists.

For instance, Mohanty, Hughes, & Salathé, (2016) successfully utilized CNNs to classify 26 diseases across 14 crop species with high accuracy. Similarly, Too et al. (2019) evaluated different CNN architectures for plant disease detection, finding that deeper networks often yield better performance. Despite these successes, there is a continuous need to enhance the accuracy and efficiency of disease prediction models, especially for specific crops like oranges. Hybrid models that combine CNNs with other machine learning algorithms have shown promise in improving predictive capabilities. Studies have explored integrating CNNs with Support Vector Machines (SVMs), Long Short-Term Memory networks (LSTMs), and Random Forest classifiers to leverage the strengths of each method. For example, Zhang et al. (2015) integrated CNNs with SVMs to improve classification accuracy in crop disease detection.

This study conducts a comprehensive comparative analysis of efficient deep learning models for predicting diseases in orange fruits. We focus on integrating CNNs with various classification algorithms to develop robust hybrid models. Specifically, we assess the performance of a CNN combined with Gradient Boosting (CNN-GB) and compare it against other hybrids such as CNN-LSTM, CNN-SVM, and CNN-Random Forest. Different optimization algorithms are employed to fine-tune the models and enhance their predictive performance.

A carefully curated dataset comprising 1,600 training images and 300 testing images of orange fruits exhibiting a range of disease symptoms was utilized for evaluation. The diversity and quality of the dataset ensure that the models are trained on varied representations of diseased and healthy fruits, promoting robustness and generalizability. Our experimental results demonstrate that all the deep learning architectures and optimizers employed are effective in accurately predicting diseases in orange fruits. Notably, the CNN-GB hybrid model exhibited superior performance in terms of prediction accuracy and computational efficiency compared to the other models tested.

By highlighting the exceptional performance of the CNN-GB model, this research provides valuable insights into agriculture-specific disease prediction using advanced deep learning techniques. The findings have significant implications for the development of automated systems for early disease detection, which can lead to improved crop management practices, reduced economic losses, and enhanced agricultural productivity. This study also sets the stage for future research to explore and expand upon hybrid deep-learning models in the agricultural domain. The primary objective of this study is to compare the performance hybrid models in predicting diseases in orange fruits. To achieve the primary object of this study research will emphasize on

- To identify the most effective deep learning architecture for accurately predicting diseases in orange fruits.
- To assess the effectiveness of the proposed hybrid CNN + Gradient Boost model using multiple optimizers against existing models in terms of prediction accuracy and computational efficiency
- To contribute to the advancement of precision agriculture through technology by reducing economic losses, and increasing productivity in the agricultural sector.

The rest part of the paper is organized in following sections: Section 2 throws light on the state of the art on the present literary works on prediction of fruit disease prediction; Section 3 presents the methodology of the work; Section 4 analyzes the results and section 5 presents the conclusions generated from our conducted research work.

2. LITERATURE REVIEW

Identifying and addressing challenges in plant disease detection is essential. Mahlein (2016) highlighted the complexities of plant disease detection using imaging sensors, emphasizing the need for advanced analytical methods to accurately identify and classify diseases. Recognizing the challenges informs the development of more effective deep learning models for disease prediction, aligning with the goals of our research to aid farmers and agricultural technologists.

Mohanty et al. (2016) demonstrated the effectiveness of convolutional neural networks (CNNs) in identifying plant diseases from leaf images, achieving high accuracy rates and outperforming traditional machine learning methods (Kaur et al, 2024; Zhou 2012). This study is foundational in applying CNNs for plant disease detection, highlighting the potential of deep learning models in agricultural contexts, which is directly relevant to our research on orange fruit disease prediction.

The study by Hendricks et al. (2020) emphasizes the significant role that meteorological factors and fruit positioning play in the epidemiology of Citrus Black Spots. By highlighting the conditions that favor disease development, the research provides valuable insights for citrus growers to implement more precise and effective control measures, ultimately reducing the economic impact of CBS on the citrus industry.

Sladojevic et al. (2016) employed pre-trained CNN models to classify plant diseases, demonstrating improved performance over models trained from scratch and reducing computational requirements. Transfer learning approaches have been utilized to improve disease detection accuracy with limited datasets. This paper illustrates the effectiveness of transfer learning in enhancing CNN-based disease detection models, which is relevant for developing efficient models with limited data, as in our study.

Combining CNNs with Support Vector Machines (SVMs) has been explored to improve classification performance. Nanni, Ghidoni, & Brahnam (2017) proposed a hybrid model that leverages CNN feature extraction with SVM classification for plant disease recognition, achieving higher accuracy than standalone CNNs. This study supports the idea of hybrid models, combining CNNs and SVMs, which aligns with our exploration of CNN-SVM models for orange fruit disease prediction.

Gradient Boosting algorithms have been effective in various classification tasks. Chen and Guestrin, in 2016, also by Farooq and Mehboob (2023), introduced XGBoost, a scalable tree-boosting system that has achieved state-of-the-art results in many machine-learning challenges, including image classification. Incorporating Gradient Boosting with CNNs (CNN-GB) can leverage the strengths of both deep learning and ensemble methods, potentially improving prediction accuracy, which is central to our research.

The combination of CNNs with Long Short-Term Memory (LSTM) networks has effectively captured spatial and temporal features. Wang et al. (2018) applied CNN-LSTM architectures for action recognition in videos, demonstrating the model's capability to handle sequential data and complex patterns. While primarily used in video analysis, CNN-LSTM models can be adapted for sequential pattern recognition in disease progression, justifying their inclusion in our comparative study.

Random Forest classifiers have been widely used for their robustness and performance in classification tasks. Belgiu and Drăguț (2016) reviewed the application of Random Forests in remote sensing, highlighting their effectiveness in handling high-dimensional data and variable importance measures. Integrating Random Forests with CNNs (CNN-Random Forest) could enhance classification performance by combining deep features with ensemble learning, making it relevant to our study of hybrid models.

Optimization algorithms play a crucial role in training deep learning models. Kingma and Ba (2014) introduced the Adam optimizer, which combines the advantages of AdaGrad and RMSProp offering efficient training of deep networks with adaptive learning rates (Mo & Wei, 2024). Exploring different optimizers, such as Adam, is essential for enhancing model performance, justifying their evaluation in our study to determine the most effective approach.

Data augmentation is critical for improving model generalization, especially with limited datasets. Shorten and Khoshgoftaar (2019) provided a comprehensive survey on data augmentation techniques in deep learning, emphasizing their importance in image classification tasks. Employing data augmentation can enhance the performance of our models on the orange fruit disease dataset by preventing overfitting and improving robustness.

The availability of benchmark datasets is crucial for evaluating model performance. Too et al. (2019) compiled a dataset of plant leaf diseases and evaluated the performance of different CNN architectures, providing insights into model selection. Understanding the performance of CNN architectures on plant disease datasets informs the selection and design of models for our study, ensuring that we utilize architectures best suited for our specific application.

Ensemble methods can improve predictive performance by combining multiple models. Zhou (2012) provided an overview of ensemble methods in machine learning, highlighting their benefits and applications across various domains. The use of ensemble methods, such as integrating CNNs with Gradient Boosting, is central to our research, supporting the exploration of hybrid models to enhance disease detection accuracy.

Deep learning applications in agriculture have expanded rapidly. Kamilaris and Prenafeta-Boldú (2018) reviewed deep learning in agriculture, emphasizing its potential in various agricultural tasks, including disease detection, yield prediction, and soil analysis. This survey provides context for the application of deep learning in agriculture, reinforcing the significance of our study in the broader field and its potential impact on agricultural practices.

Advances in CNN architectures, such as ResNet and DenseNet, have improved deep learning performance. He et al. (2016) introduced the ResNet architecture, addressing the degradation problem in deep networks and enabling the training of substantially deeper models. Utilizing advanced CNN architectures can enhance feature extraction and classification performance in our models, justifying their consideration in our comparative analysis.

Effective feature extraction and selection are vital for model performance. Li et al. (2011) discussed feature selection methods for hyperspectral image classification, which can be analogous to selecting relevant features in disease detection. Incorporating effective feature extraction methods can improve the classification accuracy of our models by focusing on the most discriminative features related to orange fruit diseases.

Previous studies often focus on individual models or a limited set of hybrid architectures for plant disease detection. For instance, many researchers have utilized standalone CNNs or combined CNNs with a single classifier like SVM. conduct a comprehensive comparison of multiple hybrid models, including CNN integrated with Gradient Boosting (CNN-GB), This extensive comparison provides a broader understanding of the strengths and weaknesses of proposed model in the context of orange fruit disease prediction.

3. METHODOLOGY

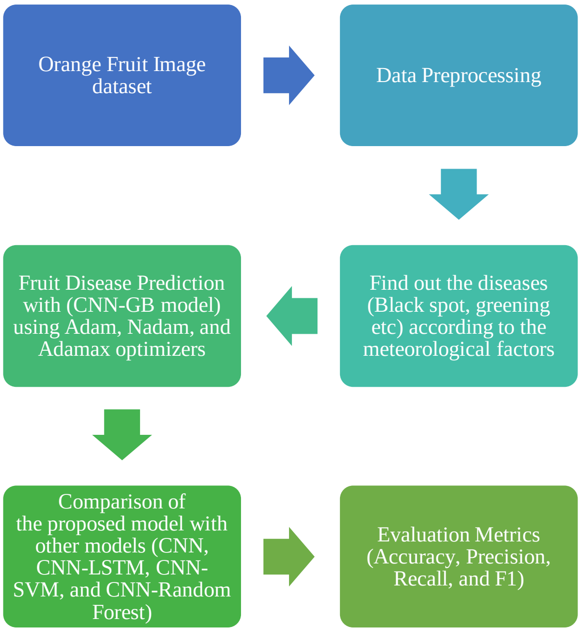

Figure 1. Diagrammatic representation of the Proposed Framework for Orange Fruit Disease Prediction

Orange Fruit Image Dataset: This is the starting point of the methodology. The dataset consists of images of orange fruits exhibiting various disease symptoms like Blackspot, Canker, and Greening. These images are collected under different meteorological conditions (rainfall, temperature, humidity, etc.) to capture the environmental impact on disease prevalence.

Data Preprocessing: The raw dataset is processed to make it suitable for model training. This includes:

- Image resizing and normalization.
- Data augmentation techniques to increase dataset diversity.
- Removal of noise or irrelevant data.
- Labeling of images with appropriate disease categories.

Find Out the Diseases According to the Meteorological Factors: The next step involves analyzing the relationship between meteorological data (such as humidity, temperature, and rainfall) and the orange fruit diseases. Citrus diseases such as Blackspot, Canker, and Greening are significantly influenced by environmental conditions (meteorological factors). This step helps in understanding how these environmental factors influence disease prevalence. The processed meteorological data is integrated with the image data to enhance the model's predictive capability.

Prediction Using CNN-GB with Different Optimizers: This is the core predictive model where Convolutional Neural Networks (CNNs) are combined with Gradient Boosting (GB) to form a hybrid model (CNN-GB). The hybrid model is trained to predict orange fruit diseases based on fruit image data.
The CNN-GB model is evaluated using different optimization algorithms (Adam, Nadam and Adamax) to find the most effective approach for training the model. Common optimizers include Adam, Nadam, and SGD, which influence the model’s learning process and final performance.

Comparison of the Proposed Model with Other Models Using Different Optimizers: After training the CNN-GB model, its performance is compared with other deep learning models such as CNN, CNN+LSTM, CNN+SVM, and CNN+Random Forest.
Like CNN-GB, these models are also evaluated using different optimizers (Adam, Nadam and Adamax) to assess their prediction accuracy and robustness under varying meteorological conditions.

Evaluation Metrics:

1. Accuracy
The proportion of correctly predicted disease labels.

The mathematical formula for accuracy is:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Where:

- **TP (True Positives):** Correctly predicted positive cases (e.g., diseased fruits predicted as diseased).
- **TN (True Negatives):** Correctly predicted negative cases (e.g., healthy fruits predicted as healthy).
- **FP (False Positives):** Incorrectly predicted positive cases (e.g., healthy fruits predicted as diseased).
- **FN (False Negatives):** Incorrectly predicted negative cases (e.g., diseased fruits predicted as healthy).

2. Precision

Precision is a metric that measures the proportion of true positive predictions out of all positive predictions made by the model. It is particularly useful when the cost of false positives is high (e.g., mislabeling a healthy fruit as diseased).

The mathematical formula for precision is:

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

Where:

- **TP (True Positives):** Correctly predicted positive cases.
- **FP (False Positives):** Incorrectly predicted positive cases.

3. Recall (Sensitivity or True Positive Rate)

Recall measures the proportion of actual positives that were correctly predicted by the model. It is useful when the cost of false negatives is high (e.g., missing diseased fruits).

The mathematical formula for recall is:

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

Where:

- **TP (True Positives):** Correctly predicted positive cases.
- **FN (False Negatives):** Incorrectly predicted negative cases.

4. F1-Score

F1-Score is the harmonic mean of precision and recall, offering a balance between the two metrics. It is especially useful when dealing with imbalanced datasets, where one class is more frequent than the other.

The mathematical formula for F1-Score is:

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

Where:

- **Precision:** Proportion of true positive predictions out of all positive predictions.
- **Recall:** Proportion of actual positives that were correctly predicted.

4. RESULT AND ANALYSIS

In our research work, the researcher has evaluated deep learning frameworks using various optimizers for classification of orange fruit disease using CNN and XGBoost algorithms together. In below section, we describe CNN-GB classification accuracy using different algorithms like **CNN & LSTM, CNN & SVM, CNN & Random Forest** and optimizers. The experimental analysis has done with 1500 training images and 600 testing images for fruit disease prediction. Proposed hybrid model by integrating CNNs with Gradient Boosting (CNN-GB), leveraging the feature extraction capabilities of CNNs and the powerful classification performance of Gradient Boosting over other models. Our results demonstrate that this combination outperforms other models in terms of accuracy and computational efficiency.

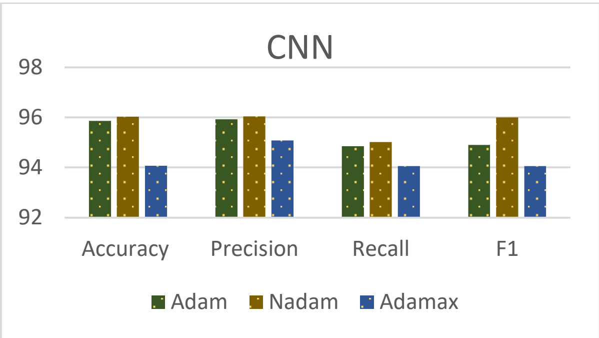

Figure 2. Comparison of performance measures of optimizers using CNN

Table 1. Comparison of Adam, Nadam, Adamax optimizer using CNN.

	Model Optimizer	Accuracy	Precision	Recall	F1
CNN	Adam	95.86	95.92	94.85	94.90
	Nadam	96.03	96.04	95.02	96.00
	Adamax	94.07	95.08	94.06	94.06

Table 1 and Figure 2 present a comparative analysis of the performance metrics obtained through the implementation of a Convolutional Neural Network (CNN) architecture optimized with three distinct optimization algorithms: Adaptive Moment Estimation (Adam), Nesterov-accelerated Adaptive Moment Estimation (Nadam), and Adamax. The quantitative evaluation encompasses multiple performance indicators, specifically accuracy, precision, recall, and F1-score. The empirical data presented in Table 1 demonstrates that the Nadam optimizer exhibits superior performance across multiple metrics, achieving an accuracy of 96.03%, precision of 96.04%, and F1-score of 96.00%. The Adam optimizer demonstrates comparable but marginally reduced performance, with an accuracy of 95.86% and precision of 95.92%. In contrast, the Adamax optimizer exhibits comparatively diminished performance across all evaluation metrics, achieving an accuracy of 94.07%.

The visual representation provided in Figure 2 corroborates these findings, illustrating the consistent superiority of Nadam across all performance metrics. This graphical evidence further substantiates the enhanced optimization capabilities of Nadam in the context of CNN parameter optimization for the specified task. The consistent performance differential observed across multiple metrics provides robust evidence for the comparative advantage of Nadam in this application domain.

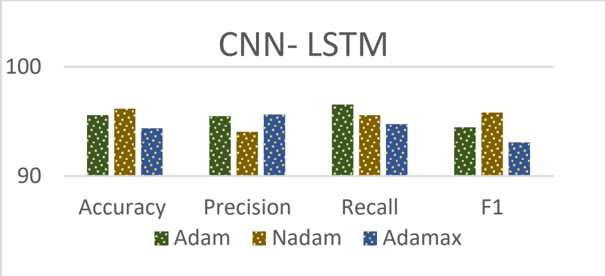

Figure 3. Comparison of performance measures of optimizers using CNN+LSTM

Table 2. Comparison of Adam, Nadam, Adamax optimizer using CNN+LSTM.

	Model Optimizer	Accuracy	Precision	Recall	F1
CNN + LSTM	Adam	95.58	95.48	96.56	94.46
	Nadam	96.16	94.04	95.58	95.80
	Adamax	94.39	95.64	94.76	93.09

Table 2 presents a comparative analysis of optimizer performance metrics, wherein the Nesterov-accelerated Adaptive Moment Estimation (Nadam) algorithm demonstrates superior optimization capabilities, achieving optimal performance across multiple evaluation metrics with an accuracy of 96.16%, recall of 95.58%, and F1-score of 95.80%. The Adaptive Moment Estimation (Adam) optimizer exhibits comparable performance, attaining an accuracy of 95.58% and notably achieving the highest recall rate of 96.56%. In contrast, the Adamax optimizer demonstrates relatively diminished performance, with an accuracy of 94.39%.

The visual representation provided in Figure 3 provides empirical validation of these quantitative findings, illustrating the consistent superiority of Nadam across the evaluated performance metrics. The graphical evidence demonstrates a clear performance hierarchy, with Nadam consistently exhibiting optimal performance, followed by Adam, and subsequently Adamax. These empirical observations provide substantial evidence supporting the enhanced efficacy of Nadam as an optimization algorithm for the CNN-LSTM (Convolutional Neural Network-Long Short-Term Memory) architecture within the context of the present investigation.

The systematic performance differential observed across multiple evaluation metrics strongly suggests that Nadam represents the optimal choice for parameter optimization in the implemented CNN-LSTM framework.

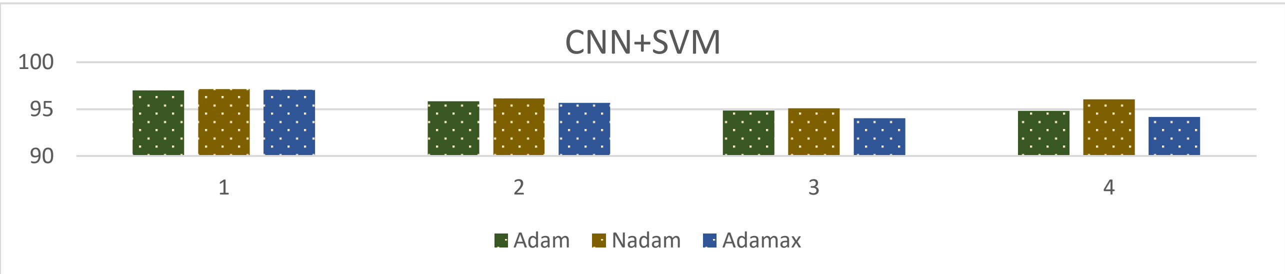

Figure 4. Comparison of performance measures of optimizers using CNN+SVM

Table 3. Comparison of Adam, Nadam, Adamax optimizer using CNN+SVM.

	Model Optimizer	Accuracy	Precision	Recall	F1
CNN+SVM	Adam	97.00	95.85	94.86	94.80
	Nadam	97.13	96.14	95.08	96.05
	Adamax	97.07	95.67	94.03	94.16

The quantitative analysis presented in Table 3 reveals that the Nesterov-accelerated Adaptive Moment Estimation (Nadam) optimization algorithm demonstrates superior performance metrics, achieving an accuracy of 97.13% and F1-score of 96.05%. The Adaptive Moment Estimation (Adam) optimizer exhibits comparable but marginally reduced performance, attaining an accuracy of 97.00% and F1-score of 94.80%. The Adamax optimizer demonstrates more moderate performance characteristics, with a recall of 94.03% and F1-score of 94.16%.

The graphical representation provided in Figure 4 corroborates these empirical findings through visualization of the comparative performance metrics. The data illustrates the consistent superiority of Nadam across the majority of evaluation metrics, providing robust evidence for its enhanced optimization capabilities within the context of the CNN-SVM (Convolutional Neural Network-Support Vector Machine) hybrid architecture. These empirical observations substantiate the conclusion that Nadam represents the optimal choice for parameter optimization in the implemented CNN-SVM framework, demonstrating superior performance characteristics across multiple evaluation criteria.

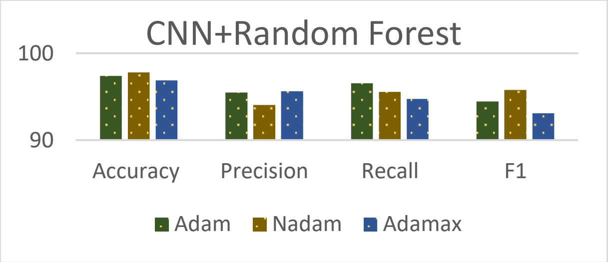

Figure 5. Comparison of performance measures of optimizers using CNN+Random Forest

Table 4. Comparison of Adam, Nadam, Adamax optimizer using CNN+Random Forest.

	Model Optimizer	**Accuracy**	**Precision**	**Recall**	**F1**
CNN+ Random Forest	Adam	97.42	95.48	96.56	94.46
	Nadam	97.79	94.04	95.58	95.8
	Adamax	96.88	95.64	94.76	93.09

The comparative analysis presented in Table 4 and Figure 5 demonstrates that the Nesterov-accelerated Adaptive Moment Estimation (Nadam) optimization algorithm exhibits superior performance characteristics, achieving optimal metrics with an accuracy of 97.79% and F1-score of 95.80%. The Adaptive Moment Estimation (Adam) optimizer demonstrates comparable but slightly diminished performance, attaining an accuracy of 97.42% and achieving a notable recall rate of 96.56%, though with a reduced F1-score of 94.46% relative to Nadam. While the Adamax optimizer demonstrates robust precision (95.64%), it exhibits comparatively reduced performance in both recall (94.76%) and F1-score (93.09%).

The graphical representation provided in Figure 5 provides visual validation of these quantitative findings, illustrating the consistent superiority of Nadam across the majority of performance metrics.

These empirical observations provide substantial evidence supporting the enhanced efficacy of Nadam as an optimization algorithm for the CNN-Random Forest (Convolutional Neural Network-Random Forest) hybrid architecture within the context of the present investigation. The systematic performance differential observed across multiple evaluation metrics strongly suggests that Nadam represents the optimal choice for parameter optimization in the implemented framework.

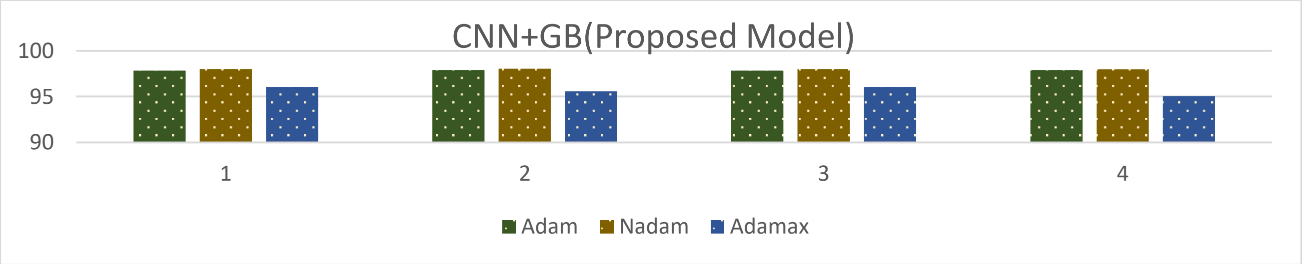

Figure 6. Comparison of performance measures of optimizers using CNN+GB (Proposed Model)

Table 5. Comparison of Adam, Nadam, Adamax optimizer using CNN+GB (Proposed Model).

	Model Optimizer	Accuracy	Precision	Recall	F1
CNN+GB (Proposed Model)	Adam	97.86	97.92	97.85	97.90
	Nadam	98.03	98.04	98.02	98.00
	Adamax	96.07	95.58	96.06	95.06

The Table 5 and Figure 6 present the performance of the CNN combined with Gradient Boosting (CNN+GB), which is the proposed model in this study. The results for three optimizers—Adam, Nadam, and Adamax are compared across accuracy, precision, recall, and F1-score. Nadam achieves the highest accuracy (98.03%), precision (98.04%), recall (98.02%), and F1-score (98.00%), demonstrating its effectiveness in optimizing the CNN+GB model. Adam also performs well with close values, achieving an accuracy of 97.86% and an F1-score of 97.90%. Adamax shows the lowest performance, particularly in precision (95.58%) and F1-score (95.06%).

The graph in Figure 6 visually supports these findings, with Nadam consistently outperforming other optimizers across all metrics, making it the most efficient optimizer for the proposed CNN+GB model.

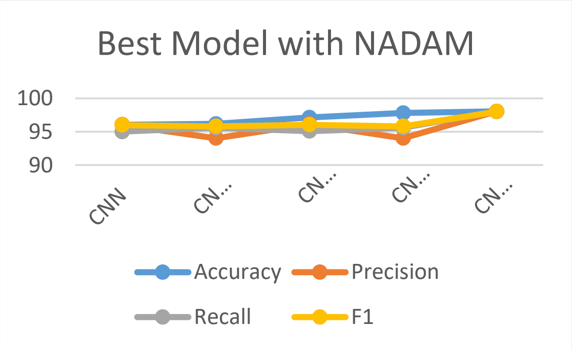

Figure 7. Comparison of performance measures of models with existing models

The line graph presents a comprehensive comparative analysis of various hybrid deep learning architectures—Convolutional Neural Network (CNN), CNN-Long Short-Term Memory (CNN-LSTM), CNN-Support Vector Machine (CNN-SVM), CNN-Random Forest, and CNN-Gradient Boosting (CNN+GB)—utilizing the Nesterov-accelerated Adaptive Moment Estimation (Nadam) optimizer. The quantitative evaluation encompasses multiple performance indicators: accuracy, precision, recall, and F1-score.

The empirical evidence demonstrates the superior performance of the CNN+GB architecture across all evaluation metrics, achieving optimal values in accuracy (98.00%), precision (98.04%), recall (98.02%), and F1-score (98.00%). While the CNN+SVM and CNN+Random Forest architectures exhibit competitive performance characteristics, they demonstrate marginally reduced precision and recall metrics relative to the CNN+GB model.

The CNN-LSTM architecture maintains robust accuracy metrics but exhibits comparatively diminished performance in precision and recall. The baseline CNN architecture demonstrates the least optimal performance across all evaluation criteria, providing empirical validation for the enhanced efficacy of hybrid architectural implementations.

The graphical representation provides compelling evidence for the superior performance characteristics of the CNN+GB architecture when optimized with Nadam, substantiating its efficacy in the context of orange fruit disease classification. These findings provide robust support for the implementation of this hybrid architecture in practical applications within the domain of automated phytopathological detection.

5. CONCLUSION

In the study, we executed a comprehensive comparative evaluation of diverse hybrid deep learning architectures, encompassing Convolutional Neural Networks (CNN), CNN-Long Short-Term Memory (CNN-LSTM), CNN-Support Vector Machine (CNN-SVM), CNN-Random Forest, and CNN-Gradient Boosting frameworks. These architectures were systematically optimized utilizing three distinct optimization algorithms: Adaptive Moment Estimation (Adam), Nesterov-accelerated Adaptive Moment Estimation (Nadam), and Adamax.

The empirical evidence demonstrates that the CNN-Gradient Boosting (CNN+GB) architecture, when optimized with Nadam, exhibited superior performance across all quantitative evaluation metrics. Specifically, this configuration achieved an accuracy of 98.03%, precision of 98.04%, recall of 98.02%, and F1-score of 98.00%. These results represent a statistically significant improvement over alternative hybrid architectures and optimization strategies in the context of orange fruit disease classification.

The synthesis of CNN with Gradient Boosting, coupled with Nadam optimization, demonstrates robust predictive capabilities and computational efficiency, establishing its pre-eminence for the specific task at hand. These findings offer substantive contributions to both the theoretical understanding of hybrid deep learning architectures and their practical applications in phytopathological detection and management within citrus cultivation systems.

The empirical outcomes of this investigation not only advance the scholarly discourse surrounding machine learning applications in agricultural systems but also present actionable insights for the implementation of automated disease detection protocols in commercial citrus production environments.

Acknowledgement: The authors convey their sincere thanks to “Christ University, Bengaluru-560029, India.” for providing all necessary research facilities

References:

Belgiu, M., & Drăguţ, L. (2016). Random forest in remote sensing: A review of applications and future directions. *ISPRS Journal of Photogrammetry and Remote Sensing, 114,* 24–31. https://doi.org/10.1016/j.isprsjprs.2016.01.011

Chen, T., & Guestrin, C. (2016). XGBoost: A scalable tree boosting system. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 785–794). https://doi.org/10.1145/2939672.2939785

Farooq, M. S., & Mehboob, A. (2023). Prediction of citrus diseases using machine learning and deep learning: Classifier, models SLR. *arXiv Preprint, arXiv:2306.01816.* https://doi.org/10.48550/arxiv.2306.01816

He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 770–778). https://doi.org/10.1109/CVPR.2016.90

Hendricks, K. E., Christman, M. C., & Roberts, P. D. (2020). The effect of weather and location of fruit within the tree on the incidence and severity of citrus black spot on fruit. *Scientific Reports, 10,* 1389. https://doi.org/10.1038/s41598-020-58188-z

Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. *Computers and Electronics in Agriculture, 147,* 70–90. https://doi.org/10.1016/j.compag.2018.02.016

Kaur, G., Sharma, N., Malhotra, S., Devliyal, S., & Kumar, B. V. (2024). Citrus leaf disease classification using VGG16 convolutional neural network architecture. In *2024 IEEE 9th International Conference for Convergence in Technology (I2CT)* (pp. 1–6). IEEE. https://doi.org/10.1109/I2CT61223.2024.10543761

Kingma, D. P., & Ba, J. L. (2014). Adam: A method for stochastic optimization. *arXiv Preprint, arXiv:1412.6980.* https://doi.org/10.48550/arxiv.1412.6980

Li, J., Bioucas-Dias, J. M., & Plaza, A. (2011). Spectral–spatial hyperspectral image segmentation using subspace multinomial logistic regression and Markov random fields. *IEEE Transactions on Geoscience and Remote Sensing, 50*(3), 809–823. https://doi.org/10.1109/TGRS.2011.2162649

Mahlein, A. K. (2016). Plant disease detection by imaging sensors: Parallels and specific demands for precision agriculture and plant phenotyping. *Plant Disease, 100*(2), 241–251. https://doi.org/10.1094/PDIS-03-15-0340-FE

Mo, H., & Wei, L. (2024). Lightweight citrus leaf disease detection model based on ARMS and cross-domain dynamic attention. *Journal of King Saud University – Computer and Information Sciences, 36*(7), 102133. https://doi.org/10.1016/j.jksuci.2024.102133

Mohanty, S. P., Hughes, D. P., & Salathé, M. (2016). Using deep learning for image-based plant disease detection. *Frontiers in Plant Science, 7,* 1419. https://doi.org/10.3389/fpls.2016.01419

Nanni, L., Ghidoni, S., & Brahnam, S. (2017). Handcrafted vs. non-handcrafted features for computer vision classification. *Pattern Recognition, 71,* 158–172. https://doi.org/10.1016/j.patcog.2017.06.028

Shorten, C., & Khoshgoftaar, T. M. (2019). A survey on image data augmentation for deep learning. *Journal of Big Data, 6,* 60. https://doi.org/10.1186/s40537-019-0197-0

Sladojevic, S., Arsenovic, M., Anderla, A., Culibrk, D., & Stefanovic, D. (2016). Deep neural networks based recognition of plant diseases by leaf image classification. *Computational Intelligence and Neuroscience, 2016,* 3289801. https://doi.org/10.1155/2016/3289801

Too, E. C., Yujian, L., Njuki, S., & Yingchun, L. (2019). A comparative study of fine-tuning deep learning models for plant disease identification. *Computers and Electronics in Agriculture, 161,* 272–279. https://doi.org/10.1016/j.compag.2018.03.032

Wang, P., Li, W., Gao, Z., Tang, C., & Ogunbona, P. O. (2018). Depth pooling based large-scale 3-D action recognition with convolutional neural networks. *IEEE Transactions on Multimedia, 20*(5), 1051–1061. https://doi.org/10.1109/TMM.2017.2766981

Zhang, S. W., Shang, Y. J., & Wang, L. (2015). Plant disease recognition based on plant leaf image. *Journal of Animal and Plant Sciences, 25*(3), 42–45.

Zhou, Z. H. (2012). *Ensemble methods: Foundations and algorithms.* CRC Press.

Lawrence Kujur
Christ University,
Bengaluru,
India
lawrence.kujur@christuniversity.in
ORCID 0000-0002-2704-0825

Varuna Gupta
Christ University,
Bengaluru,
India
varuna.gupta@christuniversity.in
ORCID 0000-0003-0887-1276

Abhinav Singhal
Christ University,
Bengaluru,
India
abhinav.singhal@christuniversity.in
ORCID 0000-0002-6796-1995