Journal of Computing & Biomedical Informatics
ISSN: 2710 - 1606
Volume 06 Issue 02
2024

Research Article
https://doi.org/10.56979/602/2024

Citrus Diseases Detection using Deep Learning

Nouman Butt[1], Muhammad Munwar Iqbal[1*] Iftikhar Ahmad[1], Habib Akbar[2], and Umair Khadam[3]

[1]Department of Computer Science, University of Engineering and Technology, Taxila, Pakistan.
[2]Department of Computer Science & IT, University of Haripur, Pakistan.
[3]Department of Software Engineering, University of Kotli AJK, Pakistan.
[*]Corresponding Author: Muhammad Munwar Iqbal. Email: munwariq@gmail.com

Received: January 04, 2024 **Accepted:** January 23, 2024 **Published:** March 01, 2024

Abstract: Pakistan is a major contributor to citrus fruit production, accounting for 30% of the total fruit output, with citrus cultivation spread across all four provinces, particularly Punjab. Citrus is vital to domestic and international markets and is distributed through various value chains. However, like many fruits, citrus is susceptible to diseases such as canker, citrus scab, and black spot, impacting fruit quality and quantity. Manual disease diagnosis in citrus fruits is time-consuming, error-prone, lacks standardization, and incurs high costs, requiring expert intervention. Accurate diagnosis and treatment are imperative for safeguarding citrus crops. The implementation of automated systems provides efficient, consistent, and cost-effective solutions, mitigating the challenges associated with manual diagnosis and contributing to sustainable citrus farming practices. This paper introduces an automated system employing Deep Learning and optimal feature selection for classifying citrus diseases. The process begins with data augmentation, enhancing the training dataset by creating additional images from existing samples. Two pre-existing models, DenseNet-201 and AlexNet, undergo adaptation and retraining utilizing an augmented dataset via transfer learning techniques. The experiment is carried out on the leaves dataset.Attaining the highest accuracy of 99.6%. The suggested framework is examined at every phase and compared to modern methods approaches, affirming its superior performance.

Keywords: Computer Vision, Data Augmentation, Features Fusion, Citrus diseases, Deep Learning.

1. Introduction

The global significance of horticulture is remarkable, as it revolves around the vital aspect of 'food,' which both humans and animals rely on. Therefore, allocating more financial support to the agricultural sector is essential. Citrus fruits hold a pivotal role in agriculture and are widely consumed by almost everyone [1]. The citrus fruit industry has a substantial presence in 137 countries, contributing significantly to the global economy. Citrus fruits are a key component of a healthy diet because of their abundant vitamin-C levels and other advantageous nutrients, offering distinct advantages to human health compared to other fruits [2]. Several citrus diseases are considered high-risk, including Anthracnose, Huanglongbing (HLB) [3], Canker, Scabies, Blackspot [4], and Sandpaper rust [5]. The manual cycle of citrus sickness discovery is perplexing because of the necessity of devoted time and regular routine ceaseless checking. Automatic detection of diseases is needed of hours. Image processing techniques are used to address this problem. However, the quality of captured images is inaccurate due to the complex environment and capturing devices.

Consequently, this limitation impacts the useful feature extraction and resultantly decreases the classification performance. The application of deep learning in agriculture sector is an active area of research for addressing disease detection and classification problems. This study introduces an automated framework that utilizes Deep Learning to classify citrus diseases and employs best feature selection methods.

Citrus diseases can cause significant misfortunes and become liable for financial misfortune because of the diminished creation and nature of citrus organic products [2]. The usage of these natural products by individuals may cause illnesses. In this way, it is significant for the ranchers to distinguish the illness in the plant before it increases to different parts. Yet, it is a troublesome and tedious interaction to watch out for each plant to identify indications of contamination at the beginning phase [3]. The manual cycle of citrus disease recognizable proof is mind-boggling because of the prerequisite of devoted time and consistent schedule continuous monitoring. In this manner, the off-base illness identifier proportion is high through a manual cycle [4]. The significant complications are vegetation disease recognition and classification. Customarily, vegetation diseases are analyzed in cultivating laboratories [5]. Existing methods and diagnostic tests for citrus infections have fallen short of meeting the agricultural sector's demands. Deep learning can potentially replace manual labor, and electronic tools have been created to both detect and prevent diseases during harvesting. Feature output serves as a major part of the CV [6] area to display the image. The fusion features and algorithm of choice that show a lot of consideration from the previous few years on CV and different techniques develop the visibility of the program [7, 8]. This paper introduces an automated Hybrid Meta-Heuristic deep learning method for classifying citrus diseases. The leading contributions are as:

- Two modified pre-trained models named DenseNet-201 and AlexNet models were trained using deep knowledge transfer.
- Features are extracted for each model; subsequently, these features are refined using the Moth-Flame Optimization Algorithm.
- The chosen features from both models are merged using an array-based technique and subsequently classified employing supervised learning classifiers like C-SVM, W-KNN, Q-SVM, LDA, F-KNN, KNB, MG-SVM, SDA, Co-KNN, and C-KNN.
- Lastly, a comprehensive comparison is discussed based on the performance of the framework.

The paper is organized as follows: Section 2 offers an overview of present and past methodologies documented in existing literature. Section 3 describes the framework for detecting and classifying citrus diseases. Section 4 contains case studies, results, and discussions. Finally, Section 5 addresses the conclusion.

2. Literature Review

Citrus disease recognition is explained and used different steps including augmentation, modified pre-trained models InceptionV3[9] and Resnet18, feature extraction [10], GA-based feature selection [11], feature fusion, and final step classification [12]. Recently, a lot of computer vision (CV) and deep learning methodologies [13] have been proposed for the augmentation and identification of plant diseases in the area of agriculture [14]. Generally, agriculture has significantly contributed to computer vision (CV) research in the past decade [15]. Numerous CV experts have devised methodologies for diagnosing and categorizing fruit diseases [16]. Their focus has centered on critical stages like the preparation phase [10] of input data processing, partial detection [17], segmentation [18], feature extraction, and ultimate categorization. Preprocessing is basically a technique [19] which is applied before any other process to improve the image quality and diminish noise and other factors which directly affects the images such as lightning, illumination and occlusion which may come when capturing images. Various preprocessing methods have been performed, including image resize, color transformation and filters such as median filter, mean filter etc. for enhancement and noise removal [20].

Utpal et al. [21] discusses varieties of convolutional neural networks (CNN) were presented. For citrus leaf separation, approaches like Self-Structured (SSCNN) and Mobile Net were implemented. Initially, the database was established using smartphones in this study. After that, both comprehensive models underwent training using identical datasets of citrus plants. Mobile Net CNN training has the highest accuracy of 98 %, with 92 % verification accuracy at 10th. During the 12th, however, the top SSCNN training accuracy was 99 %certification accuracy. The suggested method demonstrates that SSCNN is effective in real-time treating citrus leaf disease. Fangming et al. [22] introduced a functional model that utilizes innovative Conditional Opposing Auto-Encoders (CAAE) for zero-shot learning, with a focus on Citrus aurantium L. The model generates synthetic examples from both visual and non-visual categories to improve training balance. The initial citrus disease diagnosis process encompasses image manipulation, classification, methods for extracting features, selecting features, and classification.

The achieved accuracy in zero recognition stood at 53.4%, showcasing a 50.4% improvement over CVAE. The presented model is used to replace KL-divergence in different auto-encoders and is being explored for a more complex model with additional constraints, such as rotation from visual to semantic space. Sivasubramaniam et al. [23] presented a framework for detecting citrus diseases using deep metric learning, particularly designed for sparse data. This framework processes data using resource-constrained devices like mobile phones. It incorporates a network patch based on class action featuring separate modules (focus, collection, and basic neural network classes) in order to distinguish various citrus diseases. Apply a deep metric-based composition by dividing the leaf into parts. The accuracy of both types was 95.04%. They used classification accuracy as a test matrix, and the results were reported after five-fold confirmation. Future work includes the deployment of low-density models to embedded devices. In addition, network parameterization, quantization and pruning methods can be used to more compress deep models. Farah et al. [24] presented a method called 'small square drop (PLS)' for gathering elements from a set of deeply extracted features. This approach involved combining and selecting algorithms, including convolutional neural networks (CV), which improved the system's accuracy. The feature extraction method utilized VGG19's two layers (FC6 and FC7) to extract deep features related to depth, color, and texture. The PLS process was also applied in subsequent stages. The integration and selection techniques, when used with PLS, not only increased identification accuracy but also reduced computation time. The method achieved a median accuracy of approximately 90.1%.

3. Proposed Methodology

The proposed research study introduces an automated framework for the identification utilizing deep learning for diagnosing diseases in citrus leaves models. The structure of this framework is visualized in Figure 1. The procedure initiates with an initial augmentation technique that generates additional training data from the available samples. Subsequently, two pre-trained models, AlexNet and DenseNet-201, are adapted and fine-tuned through transfer learning using contrast images. Features are extracted from each model, and the feature selection process is carried out using Moth-Flame Optimization. After feature selection, the selected features are utilized for classification using Supervised Learning classifiers like Support Vector Machine (SVM) and K-nearest neighbors (KNN). The framework performance is assessed using challenging datasets and compared to existing techniques based on accuracy. Each of these stages will be detailed in the upcoming sections.

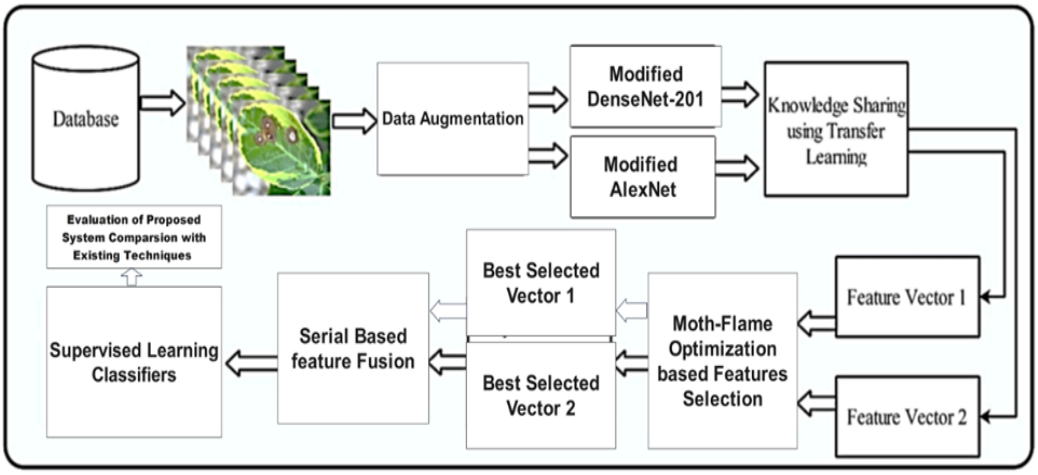

Figure 1. The proposed framework for citrus disease detection

3.1. Data Augmentation

Data augmentation is a well-known method to reduce over-fitting and enhance model performance. It involves transforming original images while preserving their key features. This technique allows the model to be trained on images from various orientations, improving its performance. It's also useful for addressing class imbalance in classification tasks. Data Augmentation is utilized in this research to mitigate the challenge of having a limited image dataset. More extensive training data typically leads to better deep-learning model performance. Three operations are rotating by 90 degrees, vertical flipping (UD), and horizontal flipping (LR). This study utilizes a Citrus Leaves dataset consisting of 609 images. Following the data augmentation procedure, the image counts expanded to 2,184 for the Citrus Leaves dataset. The augmented dataset, created through detailed data augmentation (Algorithm 1), significantly improves the training of more effective and robust DenseNet-201 and AlexNet models for leaf classification tasks. The visual representation of augmented images can be seen in Figure2.

Algorithm 1
Step 1: Load Original Dataset
Step 2: Continue Until i=4
Step 3: Operation 1 ← Left to Right Flip
Step 4: Operation 2 ← Up to Down Flip
Step 5: Rotate on 90 Degree
Step 6: Write Images of each Operation

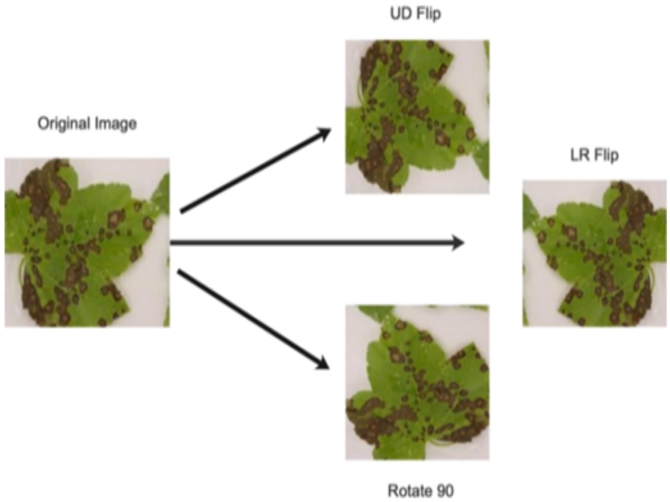

Figure 2. Data Augmentation

3.2 Deep Feature Extraction

3.2.1 Modified DenseNet201

DenseNet-201, with its 201 layers, is renowned for its deep architecture, making it well-suited for intricate image recognition tasks. Its substantial depth enables the capture of rich hierarchical features, supported by dense connectivity. Functioning as a potent feature extractor, DenseNet-201 proves beneficial in transfer learning, particularly for tasks such as classifying diseases in citrus leaves. The model's proficiency in capturing intricate representations positions it as a strong contender for image classification, especially in the context of identifying diseases in citrus leaves. The architectural details encompass 4 dense blocks and 3 transition layers, with each dense block having a growth rate of 32. Transition layers serve as bridges between blocks, incorporating convolution and pooling layers. In the fine-tuning phase, the original fully connected (FC) layer was replaced with a new FC layer. The input layer now comprises five classes, with a mini-batch size set at 64. Additionally, the learning rate, mini-batch size, and learning type parameters were configured to 0.0001 and 64. Following the updated FC layer, SoftMax and Classification layers were incorporated and linked with the previous layers. Subsequently, the modified model underwent training using transfer learning (TL). Features were extracted from the global average pooling layer, resulting in extracted features with dimensions of N × 1920. For a comprehensive understanding of the architecture, further details are available in the presented Figure 3.

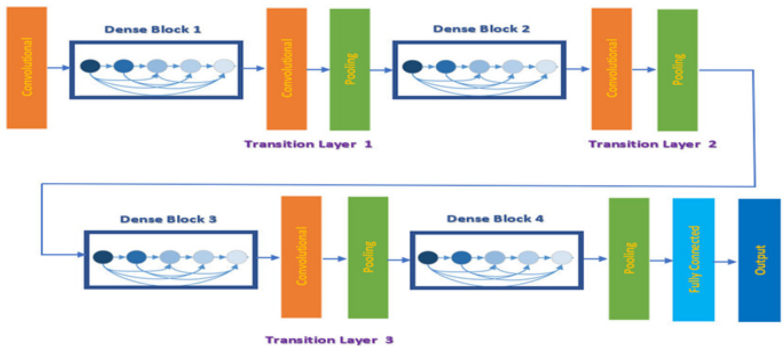

Figure 3. Schematic diagram DenseNet-201 model Architecture

3.2.2 Modified AlexNet

AlexNet is a groundbreaking Convolutional neural network (CNN) primarily used for image recognition and classification. It comprises eight layers with learnable parameters. The model includes five layers with a sequence of max pooling followed by three fully connected layers, all employing ReLu activation, except for the output layer. Utilizing ReLu as an activation function enhanced the training speed by approximately sixfold. They integrated dropout layers as a measure to prevent over-fitting. The model underwent training using the Image-Net dataset, which contains nearly 14 million images distributed across a thousand classes.AlexNet is a deep neural network, and its creators added padding to maintain the size of feature maps during processing. This model's input images are 227x227 pixels and have three color channels. In the fine-tuning phase, the original fully connected (FC) layer was replaced with a new FC layer. The input layer now comprises five classes, with a mini-batch size set at 64. Additionally, the learning rate, mini-batch size, and learning type parameters were configured to 0.0001 and 64. Following the updated FC layer, SoftMax and Classification layers were incorporated and linked with the previous layers. Subsequently, the modified model underwent training using transfer learning (TL). Features were extracted from the global average pooling layer, resulting in extracted features with dimensions of N × 1092 This is visualized in Figure 4.

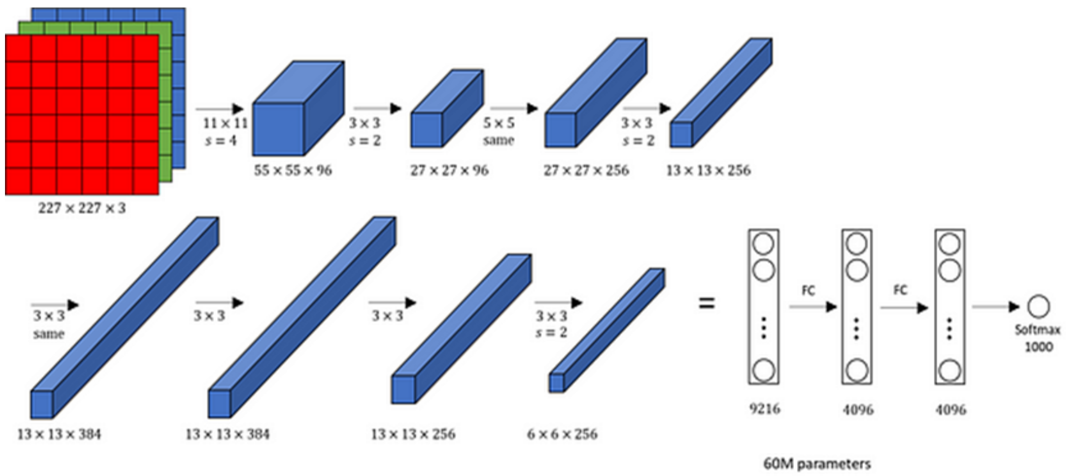

Figure 4. Diagram of AlexNet Architecture

The rationale for choosing DenseNet-201 and AlexNet lies in their architectural strengths, adaptability for transfer learning, and established success in image classification tasks. The combination of dense connectivity, spatial feature capturing, and efficient transfer learning contributes to the success of the automated system in accurately classifying and diagnosing diseases in citrus leaves.

3.3 Feature Selection using Moth Flame Optimization

In 2015, Mirjalili[25] developed "Moth-Flame Optimization algorithm". This algorithm was developed to address intricate global optimization issues and was based on a mathematical model that mimicked the moths' spiral flight behavior around artificial lights. In this approach, moth positions change over a series of predetermined iterations. In the initial iteration, moths are randomly scattered across the problem space. The position of each moth is determined by a mathematical equation (2), where X_{id} represents the dth size of the ith position of the moth and its parameters Ub_d and $Lb_d$the maximum and minimum limits for thedth dimension, respectively.

$$X_{id} = rand_{i,d} \times (Ub_d - Lb_d) + Lb_d, \qquad 1 \leq d \leq D \tag{2}$$

In the subsequent iterations, the moths' positions change by being influenced by the location of a "flame". The flame number (R). Throughout subsequent iterations, their updated positions rely on the flame's position. Thus, the flame number (R) is calculated using a specific), taking into account parameters like the number of moths N and the maximum number of iterations (MaxIterations). The positions of the flames are subsequently established using a step-by-step procedure detailed in Algorithm 2.

Algorithm 2. The process of creating flames within the optimization

Input data The algorithm utilizes various input data, including the locations of moths represented by X, the fitness values of moths denoted as Fit, the position of the flame denoted as F, and the fitness values of flames represented by OF(t). The process of building the flame matrix involves distinct steps during the first iteration (t = 1) and subsequent iterations (t > 1).
First Iteration (t = 1): 1. Sort the Fit vector in increasing order, identifying the arranged indices as {j_1, j_2, …, j_N}. 2. Build the flame matrix F(t)={F_1←X_j1, F_2←X_j2, …, F_N←X_jN}. **Subsequent Iterations (t > 1):** 1. Create a composite matrix Dual_Pop by combining matrices F(t) and X(t-1). 2. Form a vector named Dual_Fit by combining matrices OF(t) and Fit(t-1). 3. Arrange the vector Dual_Fit in ascending order and retrieve the sorted index within {j_1, j_2, …, j_2N}. 4. Create the flame matrix F(t)={F_1←X_j1, F_2←X_j2, …, F_N←X_jN} based on the sorted indices. This iterative process helps refine the flame matrix in subsequent iterations, incorporating information from both moths and flames, contributing to the optimization of the algorithm over time.

DenseNet-201 and AlexNet. This process results in the selection of the two best feature vectors, which are combined through array-based concatenation, defined mathematically as follows:

$$Fus(a) = \{Vec(1); Vec(2)\}_{N \times A} \tag{3}$$

In the equation (3), $Fus(a)$ represent ath feature of the combined feature vector, $Vec(1)$ denotes the initial chosen feature vector, $Vec(2)$ is followed by the second selected feature vector, and $N \times A$ represents the ultimate dimension of a merged feature vector. This final feature vector is then used as input for supervised learning algorithms in the final classification process.

4. Experimental Analysis and Results

The presented framework undergoes assessment using the publicly accessible citrus leaves dataset with 2184 images of diseases, including Citrus Greening (408 images), Blackspot (684 images), Canker (652 images), Melanose (208 images), and Healthy (232 images) samples. The inherent characteristics of the images in the data set are in RGB format with sizes of 224x224x3 and 227x227x3 for DenseNet-201 and AlexNet, respectively. The 70% of the images are allocated for training, and the remaining 30% are utilized for testing. Results for each dataset are determined through 10-fold cross-validation. Multiple classifiers are utilized, and the one with the highest accuracy is selected, validating the proposed method. All simulations are performed on MATLAB R2020a, and performance evaluation metrics include Sensitivity (True Positive Rate), specificity (True Negative Rate), Precision (Positive Predictive Value), Accuracy, Area under Curve (AUC), and False Positive Rate (FPR). The outcomes are derived from five experiments: a) Classification with fine-tuned DenseNet-201, b) Classification with fine-tuned AlexNet, c) Classification using the best features of fine-tuned DenseNet-201, d) Classification using the best features of fine-tuned AlexNet, and e) Classification of the fusion of best features. 10 classifiers, namely C-SVM, W-KNN, Q-SVM, LDA, F-KNN, KNB, MG-SVM, SDA, Co-KNN, and C-KNN are employed to authenticate the suggested models and the best among them is selected based on accuracy. The results of five experiments are given in Figures 5 to 7 & Table 1. A comparison of the results of the suggested framework to the most current advanced techniques is given in Table 2.

4.1 Discussion

The results of the experiments (a) and (b) are shown in Figure 5 & 6, indicating that the Quadratic SVM classifier attained the highest accuracy within both cases, with 98.9% accuracy using DenseNet-201 and 94.3% accuracy using AlexNet. Additionally, we found that the processing time during testing varied among classifiers. For the DenseNet-201 features, the Quadratic SVM had the shortest time of 13.294 seconds, while for AlexNet features, it was 38.894 seconds. The conclusion about the performance comparison between the fine-tuned DenseNet-201 and AlexNet models is that DenseNet-201 outperformed AlexNet regarding both accuracy and processing time. The DenseNet-201 model achieved greater accuracy and faster processing times compared to AlexNet for this classification task on the Leaves dataset. Results of experiment (c) are shown in Figure 7, indicating that the Cubic SVM classifier achieved the highest accuracy of 98.7% with the shortest processing time of 9.3562 seconds, whereas the highest time was 142.47 seconds for the Kernel Naive Bayes classifier. Similarly, the classification was performed on the best features obtained from fine-tuned AlexNet, i.e., experiment (d). The results are shown in Figure 8, with Cubic SVM achieving the highest accuracy of 94.1% with the shortest processing time of 21.472 seconds, exhibiting considerable improvement compared to the time specified in Figure 5.

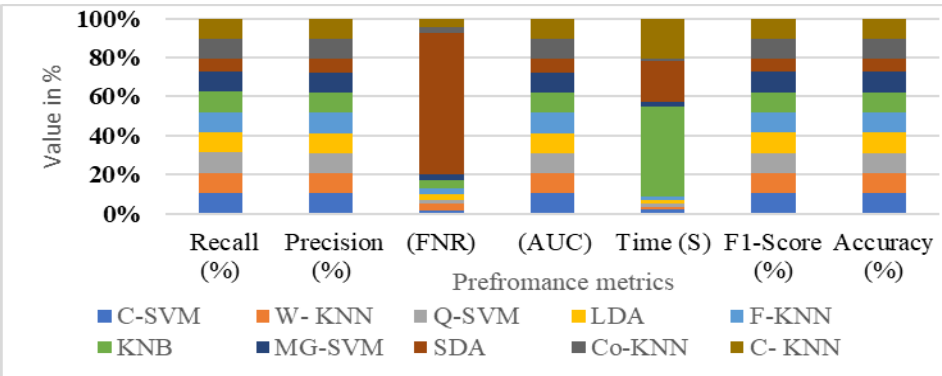

Figure 5. Leaves dataset classification results achieved with fine-tuned DenseNet-201

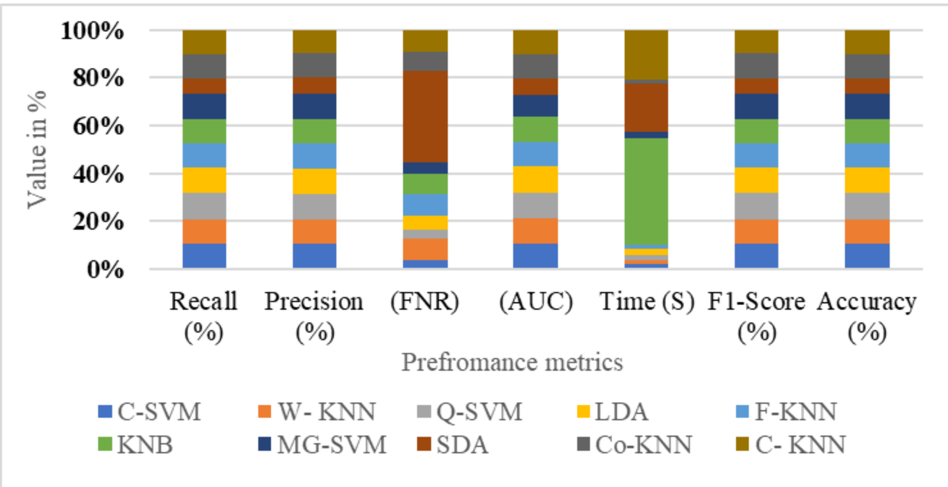

Figure 6. Leaves dataset classification results achieved with fine-tuned AlexNet

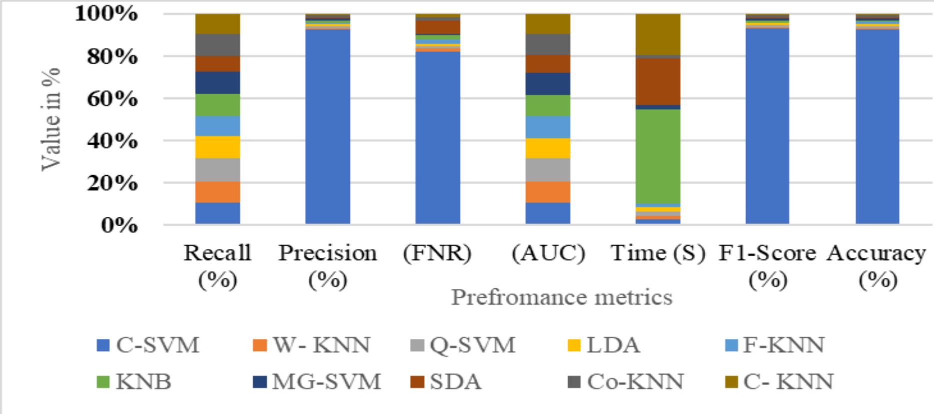

Figure 7. Leaves dataset classification results using the best features of fine-tuned DenseNet-201

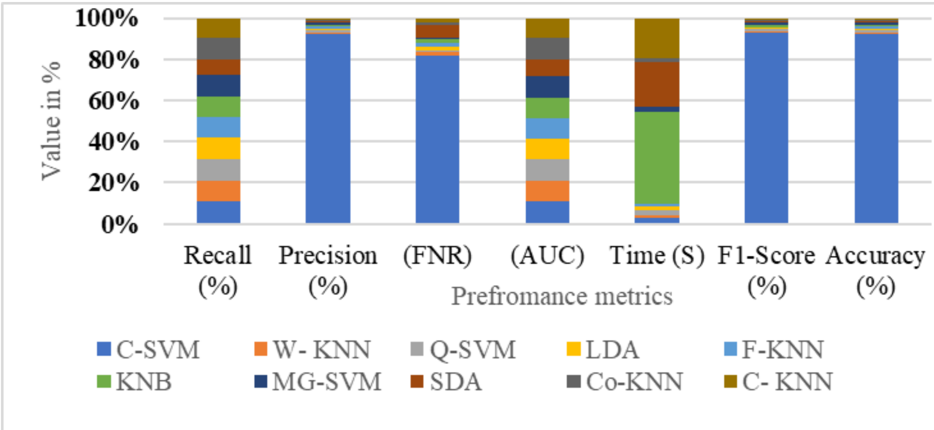

Figure 8. Leaves dataset classification results using the best features of fine-tuned AlexNet

Table 1. Leaves dataset classification results achieved through the fusion of best features

Classifiers	Recall (%)	Precision (%)	(FNR)	(AUC)	Time (S)	F1-Score (%)	Accuracy (%)
C-SVM	99.2%	99.2%	7.8%	0.994	81.566	99.2%	99.1%
W- KNN	97.88%	97.2%	2.12%	0.972	47.633	97.0%	96.7%
Q-SVM	99.2%	99.2%	0.8%	0.994	67.09	99.2%	99.1%
LDA	99.64%	99.72%	0.36%	0.998	78.263	99.6%	99.6%
F-KNN	97.14%	97.84%	2.86%	0.978	48.118	97.4%	96.9%
KNB	97.14%	96.92%	2.86%	0.968	1205.1	97.02%	96.6%
MG-SVM	98.46%	98.28%	1.54%	0.984	78.75	98.3%	98.2%
SDA	50.6%	52.9%	49.4%	0.53	519.85	51.7%	45.1%
Co-KNN	95.96%	95.66%	4.04%	0.956	56.73	95.8%	95.2%
C-KNN	97.08%	96.9%	2.92%	0.972	479.02	97.0%	96.9%

In the conclusive experiment, merged the best features chosen from both deep models through a fusion technique Table 1 shows the results indicating that linear discrimination achieves the best accuracy of 99.6%. In this experiment, the second-highest accuracy reached is 99.1%, accomplished by the Quadratic SVM classifier. Compared to Figures 5-8, the accuracy obtained through fusion shows significant improvement. However, potential limitations include challenges in generalizing the model to diverse environmental conditions and addressing dataset biases. Future research should focus on enhancing model robustness, incorporating more diverse datasets, and exploring interpretability techniques for broader agricultural applications. Comparison of the proposed model with recent techniques better shows the promise of this model.

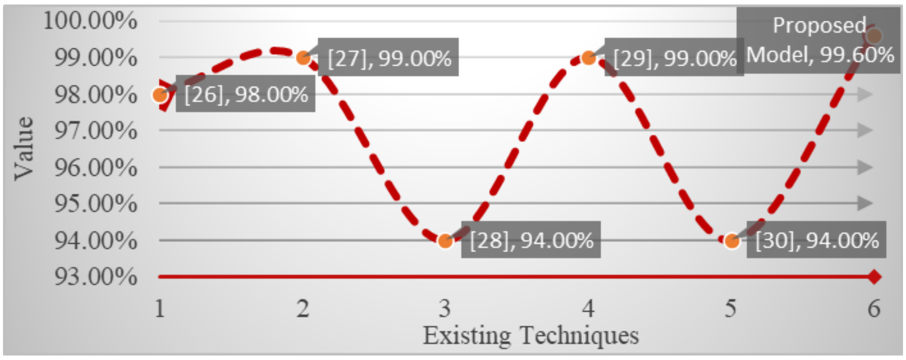

Figure 9. Comparisons with Existing Techniques

Table 2 and Figure 9 support the abstract claims the proposed model achieves the highest accuracy of 99.6%.

Table 2. Comparisons with Existing Techniques on Leave Dataset

Reference	Year		Accuracy (%)
[26]	2021	Leaves Dataset	98.0%
[27]	2021	Leaves Dataset	99.0%
[28]	2022	Leaves Dataset	94.0%
[29]	2022	Leaves Dataset	99.0%
[30]	2023	Leaves Dataset	94.0%
Proposed Model	**2023**	**Leaves Dataset**	**99.6%**

The suggested framework is thoroughly compared with existing methods, emphasizing the superiority of the DenseNet-201 model in citrus leaf disease detection. The analysis focuses on accuracy and processing time metrics, showcasing DenseNet-201 better performance compared to alternatives like AlexNet. This nuanced understanding affirms the framework's effectiveness in modern approaches for citrus leaf disease classification.

5. Conclusions

Deep learning has made remarkable strides in agriculture, notably in its ability to automate the identification of plant diseases while reducing the need for extensive human involvement. This research aimed to create an automated system for disease identification in Citrus leaves employing deep learning and best feature selection. Data augmentation is executed during the early stages to expand the dataset and enhance the robustness of deep learning models. Subsequently, two models that underwent pre-training were adapted and fine-tuned using transfer learning on the augmented datasets. Features were extracted through a proposed Moth-Flame Optimization (MFO) method and combined employing a sequential-based method. The obtained features were subsequently categorized using diverse Supervised Learning algorithms. The fusion of the chosen Deep features notably enhances detection accuracy, but this enhancement is accompanied by a trade-off of increased computational time.

Acknowledgments: I am grateful to my teacher Dr. Muhammad Munwar Iqbal who made this work possible and whose contribution to my post graduate experience will always be remembered.

References

1. H. Zhang, Y. Chen, X. Liu, Y. Huang, B. Zhan, and W. Luo, "Identification of Common Skin Defects and Classification of Early Decayed Citrus Using Hyperspectral Imaging Technique," Food Analytical Methods, pp. 1-18, 2021.
2. C. Mattihalli, E. Gedefaye, F. Endalamaw, and A. Necho, "Plant leaf diseases detection and auto-medicine," Internet of Things, vol. 1, pp. 67-73, 2018.
3. L. J. Klotz and H. S. Fawcett, "Color handbook of citrus diseases," Color handbook of Citrus diseases. Second edition., 1948.
4. W. G. Lima, M. B. Spósito, L. Amorim, F. P. Gonçalves, and P. A. M. de Filho, "Colletotrichum gloeosporioides, a new causal agent of citrus post-bloom fruit drop," European Journal of Plant Pathology, vol. 131, no. 1, pp. 157-165, 2011.
5. A.-K. Mahlein, U. Steiner, H.-W. Dehne, and E.-C. Oerke, "Spectral signatures of sugar beet leaves for the detection and differentiation of diseases," Precision agriculture, vol. 11, no. 4, pp. 413-431, 2010.
6. A. Timmermans, "Computer vision system for on-line sorting of pot plants based on learning techniques," in II International Symposium On Sensors in Horticulture 421, 1995, pp. 91-98.
7. S. Qadri et al., "Machine vision approach for classification of citrus leaves using fused features," International Journal of Food Properties, vol. 22, no. 1, pp. 2072-2089, 2019.
8. X. Teng and Y. Gong, "Research on application of machine learning in data mining," in IOP conference series: materials science and engineering, 2018, vol. 392, no. 6: IOP Publishing, p. 062202.
9. J. Chen, J. Chen, D. Zhang, Y. Sun, and Y. A. Nanehkaran, "Using deep transfer learning for image-based plant disease identification," Computers and Electronics in Agriculture, vol. 173, p. 105393, 2020.
10. S. D. Khirade and A. Patil, "Plant disease detection using image processing," in 2015 International conference on computing communication control and automation, 2015: IEEE, pp. 768-771.
11. S. Phadikar, J. Sil, and A. K. Das, "Rice diseases classification using feature selection and rule generation techniques," Computers and electronics in agriculture, vol. 90, pp. 76-85, 2013.
12. H. Al-Hiary, S. Bani-Ahmad, M. Reyalat, M. Braik, and Z. Alrahamneh, "Fast and accurate detection and classification of plant diseases," International Journal of Computer Applications, vol. 17, no. 1, pp. 31-38, 2011.
13. N. O'Mahony et al., "Deep learning vs. traditional computer vision," in Science and Information Conference, 2019: Springer, pp. 128-144.
14. Q. Wu, Y. Chen, and J. Meng, "DCGAN-based data augmentation for tomato leaf disease identification," IEEE Access, vol. 8, pp. 98716-98728, 2020.
15. T. K. Hariadi, Z. Fadholi, A. N. Chamim, N. A. Utama, I. Prabasari, and S. Riyadi, "Development of Leaf Area Meter Using Open CV for Smartphone Application," Telkomnika, vol. 16, no. 4, pp. 1857-1863, 2018.
16. Z. Iqbal, M. A. Khan, M. Sharif, J. H. Shah, M. H. ur Rehman, and K. Javed, "An automated detection and classification of citrus plant diseases using image processing techniques: A review," Computers and electronics in agriculture, vol. 153, pp. 12-32, 2018.
17. J. G. A. Barbedo, "Digital image processing techniques for detecting, quantifying and classifying plant diseases," SpringerPlus, vol. 2, no. 1, pp. 1-12, 2013.
18. V. Singh and A. K. Misra, "Detection of plant leaf diseases using image segmentation and soft computing techniques," Information processing in Agriculture, vol. 4, no. 1, pp. 41-49, 2017.
19. J. Park, Y.-W. Tai, D. Cho, and I. So Kweon, "A unified approach of multi-scale deep and hand-crafted features for defocus estimation," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2017, pp. 1736-1745.
20. R. Malladi and J. A. Sethian, "A unified approach to noise removal, image enhancement, and shape recovery," IEEE Transactions on Image Processing, vol. 5, no. 11, pp. 1554-1568, 1996.
21. U. Barman, R. D. Choudhury, D. Sahu, and G. G. Barman, "Comparison of convolution neural networks for smartphone image based real time classification of citrus leaf disease," Computers and Electronics in Agriculture, vol. 177, p. 105661, 2020.
22. F. Zhong, Z. Chen, Y. Zhang, and F. Xia, "Zero-and few-shot learning for diseases recognition of Citrus aurantium L. using conditional adversarial autoencoders," Computers and Electronics in Agriculture, vol. 179, p. 105828, 2020.
23. S. Janarthan, S. Thuseethan, S. Rajasegarar, Q. Lyu, Y. Zheng, and J. Yearwood, "Deep metric learning based citrus disease classification with sparse data," IEEE Access, vol. 8, pp. 162588-162600, 2020.
24. F. Saeed, M. A. Khan, M. Sharif, M. Mittal, L. M. Goyal, and S. Roy, "Deep neural network features fusion and selection based on PLS regression with an application for crops diseases classification," Applied Soft Computing, vol. 103, p. 107164, 2021.
25. Mirjalili, Seyedali. "Moth-flame optimization algorithm: A novel nature-inspired heuristic paradigm." Knowledge-based systems 89 (2015): 228-249.
26. N. E. M. Khalifa, M. H. N. Taha, L. M. Abou El-Maged, and A. E. Hassanien, "Artificial Intelligence in Potato Leaf Disease Classification: A Deep Learning Approach," in Machine Learning and Big Data Analytics Paradigms: Analysis, Applications and Challenges, ed: Springer, 2021, pp. 63-79
27. X. Chen, G. Zhou, A. Chen, L. Pu, and W. Chen, "The fruit classification algorithm based on the multi-optimization convolutional neural network," Multimedia Tools and Applications, vol. 80, pp. 11313-11330, 2021.
28. Elaraby, Ahmed, Walid Hamdy, and Saad Alanazi. "Classification of citrus diseases using optimization deep learning approach." Computational Intelligence and Neuroscience 2022 (2022).

29. Majid, Abdul, et al. "An Integrated Deep Learning Framework for Fruits Diseases Classification." Computers, Materials & Continua 71.1 (2022).
30. Kukreja, Vinay, Rishabh Sharma, and Rishika Yadav. "Improving Citrus Farming Through Efficient and Accurate Diagnosis of Lemon Citrus Canker Disease with Deep Learning." 2023 4th International Conference for Emerging Technology (INCET). IEEE, 2023.