Exploring Transfer Learning Models for Multi-Class Classification of Infected Date Palm Leaves

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***Abstract*— This research explores the feasibility of leveraging transfer learning models, including AlexNet, VGGNet, and ResNet, alongside a newly devised Convolutional Neural Network (CNN) architecture, for the accurate multi-class classification of infected date palm leaves. The research harnesses the power of transfer learning by adapting these established models to the task of identifying various types of infections in date palm leaves. Alongside, a custom CNN is introduced, designed to capture intricate disease-related patterns and outperform generic architectures. Rigorous experimentation on a carefully annotated dataset enables a comprehensive performance comparison in terms of accuracy, precision, recall, F1 score, and computational efficiency. This investigation not only advances automated plant disease detection but also emphasizes the significance of specialized models in agricultural technology, contributing to sustainable food production and resource preservation.**

Keywords*— *Transfer Learning, Multi-Class Classification, Infected Date Palm Leaves, Convolutional Neural Network (CNN), Plant Disease Detection, Sustainable Agriculture.

I. Introduction

Plant diseases have been a persistent challenge in agriculture, causing substantial economic losses and threatening global food security. In particular, the health of date palm trees, which hold cultural, economic, and ecological significance, is jeopardized by various diseases. Early and accurate detection of these diseases is crucial for effective disease management. Traditional methods of disease identification often require expert knowledge and significant time investment. However, recent advances in deep learning, particularly in the field of computer vision, have shown promising results in automating disease detection and classification across different crops.

This research aims to address the intricate task of classifying infected date palm leaves using advanced deep learning techniques. Specifically, we investigate the application of state-of-the-art transfer learning models, namely AlexNet, VGGNet, and ResNet, for this task. Transfer learning leverages pre-trained neural network architectures trained on large datasets, enabling effective feature extraction even with limited labeled data. Additionally, recognizing the unique challenges of date palm disease classification, we propose a domain-specific Convolutional Neural Network (CNN) architecture tailored to capture the subtle characteristics of various infections.

By conducting thorough experimentation and performance evaluation on a meticulously annotated dataset, this study seeks to contribute to the field of automated plant disease detection. The outcomes of this research have implications for enhancing agricultural practices, promoting sustainable food production, and mitigating the impact of plant diseases on a global scale.

II. Related Works

M. Ahmed and A. Ahmed [1] embark on an exploration of disease detection within the realm of palm trees. Their innovative approach intertwines residual networks and transfer learning of inception ResNet. By leveraging these techniques, they aim to fortify disease classification accuracy. Through the interplay of cutting-edge architectures and transfer learning, their study contributes to enhancing the efficiency of identifying diseases that afflict palm trees, a critical concern in the realm of agriculture.

M. Shoaib et al. [2] traverse the landscape of plant disease detection using deep learning models. In their comprehensive review, they encapsulate the ever-evolving trends in this field, spotlighting the surge in research endeavors. By investigating an array of advanced deep learning models, they bring forth a panoramic view of recent breakthroughs. This work resonates as an essential repository of knowledge, offering a nuanced understanding of the progress and challenges in utilizing these advanced techniques for plant disease detection.

K. M. Hosny et al. [3] present an intricate framework for addressing multi-class plant leaf disease classification. Through a melding of deep convolutional neural networks and local binary pattern features, they establish a novel approach that capitalizes on feature fusion. This holistic strategy underscores their dedication to achieving heightened classification accuracy, a feat crucial for effective disease management. By forging a synergy between different computational methodologies, their work showcases the multidisciplinary essence of disease classification research.

A. M. AL-Mahmood, H. I. Shahadi, and A. R. Hasoon Khayeat [4] usher in a pivotal contribution with their provision of an image dataset depicting infected date palm leaves caused by dubas insects. This dataset, meticulously curated, serves as a cornerstone for researchers and practitioners immersed in the realm of plant disease detection. By offering a tangible resource, their work fosters the development of more accurate and robust detection models, acting as a catalyst for advancements in tackling this specific disease affliction.

A. Hessane et al. [5] venture into the realm of stage-wise classification for date palm white scale disease. Their research heralds the amalgamation of feature extraction techniques with machine learning methodologies. This stage-wise perspective enriches disease management strategies by discerning various disease progression phases. Their contribution signifies an innovative stride in disease classification research, positioning them at the crossroads of technology and agricultural sustainability.

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K. Harshavardhan et al. [6] embark on a journey focused on automating the identification of diverse plant leaf diseases. Through the prism of deep learning techniques, they present an array of approaches aimed at enhancing disease detection accuracy. By demonstrating the application of neural networks in tackling this intricate task, they open avenues for scalable and efficient disease management solutions.

N. Nafiiyah et al. [7] introduce an intriguing approach by harnessing the power of majority voting transfer learning CNN for peanut leaf type identification. This ensemble-based strategy showcases innovation in aggregation methodologies. By amalgamating diverse deep learning outputs, their work endeavors to push the boundaries of classification accuracy, rendering their contribution a testament to the amalgamation of traditional and contemporary techniques.

Z. Wu, F. Jiang, and R. Cao [8] illuminate the landscape of leaf disease recognition within woody fruit plants. Their research focuses on recognition methods based on transfer learning, underscoring the adaptability of deep learning paradigms to diverse plant species. By delving into a specific niche of plant diseases, their work contributes to enriching the understanding of disease recognition in a broader botanical context.

A. M. Al-Mahmood, H. I. Shahadi, and A. R. H. Khayeat [9] set their sights on a specific challenge, delving into the classification of infected palms with dubas bugs. Their work underscores the application of artificial intelligence in addressing niche disease scenarios, highlighting the interdisciplinary nature of disease detection. By narrowing their focus, they offer insights into customizing approaches for unique plant-disease interactions.

A. Hessane et al. [10] present a meticulous methodology for classifying date palm white scale disease. Their technique involves the extraction of pertinent features, closely intertwined with machine learning methodologies. This stage-wise approach enriches disease detection accuracy, providing valuable insights into the progression dynamics of the disease. Their work transcends generic classifications, reflecting a nuanced approach to disease management.

Ü. Atila et al. [11] put forth a novel deep learning model, EfficientNet, as a formidable contender for plant leaf disease classification. Their study demonstrates a commitment to exploring a diverse array of neural network architectures to optimize disease detection accuracy. By experimenting with novel architectures, they contribute to the ongoing dialogue surrounding the selection and adaptation of deep learning models in the context of plant diseases.

J. Gu, P. Yu, X. Lu, and W. Ding [12] embark on a journey of leaf species recognition, drawing inspiration from VGG16 networks and transfer learning techniques. Their research unfurls the utilization of pre-trained models for the intricate task of leaf disease identification. By elucidating the intersection of architectural prowess and transfer learning, their work showcases a pathway to optimized disease recognition.

H. Alaa et al. [13] carve a unique niche by amalgamating image processing and machine learning techniques for detecting palm tree diseases. This interdisciplinary approach underscores the potential of technology in addressing real-world agricultural challenges. By bridging the gap between agricultural concerns and technological solutions, their work serves as a testament to the transformative power of integrating different domains.

R. Nishad and T. A. Ahmed [14] offer a comprehensive survey that delves into the spectrum of date palm pathogens and indigenous biocontrol agents. Their work resonates as a critical contribution, shedding light on disease management strategies and offering a holistic understanding of the biological interactions at play. By conducting a meticulous survey, they lay the groundwork for more informed disease management methodologies.

A. Magsi et al. [15] embark on an exploratory journey, unraveling the intricacies of date palm disease identification. Their study marries features extraction with deep learning techniques, culminating in a methodology primed for accurate disease detection. By scrutinizing the amalgamation of traditional and contemporary approaches, their work attests to the dynamic nature of disease detection research.

K. J. Alwahshi et al. [16] contribute to the discourse on date palm diseases by unraveling the molecular intricacies of the sudden decline syndrome. Their research underscores the significance of understanding the genetic and molecular underpinnings of diseases. By delving into the molecular realm, they provide valuable insights for formulating disease management strategies that are rooted in the biological intricacies of the affliction.

III. METHODOLOGY FOR TRASNFER LEARNING

The methodology employed in this study to leverage the potential of transfer learning for the classification of infected date palm leaves involves a series of purposeful steps designed to align pre-trained neural network models with the specific task of disease detection.

A. Curating the Dataset:

The foundation of this methodology rests on the careful curation of a comprehensive dataset of infected date palm leaves. The dataset encompasses a diverse range of infections, meticulously labeled to facilitate accurate model training.

B. Selection of Pre-trained Models:

Esteemed deep neural network architectures, including AlexNet, VGGNet, and ResNet, are strategically chosen for their established effectiveness in image recognition tasks.

C. Initializing with Pre-trained Weights:

The chosen architectures are initialized with pre-trained weights obtained from extensive training on datasets like ImageNet. These initial weights encapsulate valuable image features learned through layers of hierarchical abstraction.

D. Tailoring Model Layers:

The core of transfer learning lies in adapting pre-trained models to the specific task. In this step, the initial layers, responsible for recognizing generic features, are retained. However, the deeper layers are selectively modified to capture patterns relevant to date palm infection classification.

E. Training and Validation:

The adapted models undergo rigorous training on the curated dataset. Concurrently, a validation set is utilized to monitor their progress and performance. This step ensures that the models are learning relevant features and generalizing effectively.

F. Thorough Evaluation:

After training, the models are subjected to a comprehensive evaluation process using a separate test dataset. Performance metrics such as accuracy, precision, recall, F1 score, and confusion matrices are employed to assess their proficiency in classifying various types of infected date palm leaves.

G. Innovative CNN Architecture:

Alongside established models, a novel Convolutional Neural Network (CNN) architecture tailored to date palm diseases is introduced. This architecture aims to capture intricate infection-related patterns that could outperform generic models in terms of accuracy.

The provided architecture defines a Convolutional Neural Network (CNN) for classifying images of infected date palm leaves. It begins with an input layer for 224x224 RGB images, followed by two convolutional layers with ReLU activation and max-pooling to extract features. Dropout layers are inserted to prevent overfitting. After flattening, two fully connected layers follow, with the first having 128 units and ReLU activation, mitigated by dropout. The output layer with SoftMax activation produces probabilities for the four leaf classes. The model is compiled with categorical cross-entropy loss, optimized using 'adam,' and evaluated with accuracy. This design facilitates the extraction of intricate patterns in the images, enabling effective classification of diverse infected date palm leaves.

By integrating these methodical steps, the transfer learning methodology aims to enhance the automated detection of infected date palm leaves. Through thorough execution and evaluation, the goal is to contribute to agricultural sustainability by enabling accurate disease detection and management.

IV. Result and Analysis

Leaf images were classified into four categories based on health and insect presence: healthy, bug-infected, honeydew-infected, and mixed insect-honeydew infection. Covering insect life cycle stages from nymphs to adults, the dataset of 3000 images, captured by two drones, includes 800 per non-bug category and 600 bug images. The dataset is valuable for gauging infestation severity, insect populations, and damage extent.

link: https://data.mendeley.com/datasets/2nh364p2bc/2

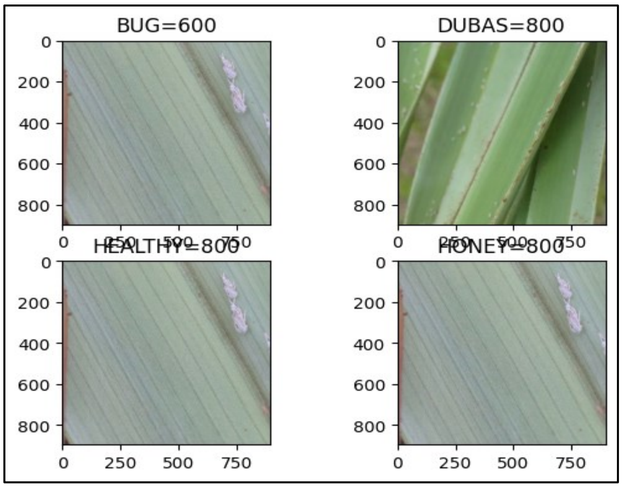

Fig. 1. Reding Dataset

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_5 (Conv2D)           (None, 54, 54, 96)        34944

 batch_normalization_5 (Batc  (None, 54, 54, 96)       384
 hNormalization)

 max_pooling2d_3 (MaxPooling  (None, 26, 26, 96)       0
 2D)

 conv2d_6 (Conv2D)           (None, 26, 26, 256)       614656

 batch_normalization_6 (Batc  (None, 26, 26, 256)      1024
 hNormalization)

 max_pooling2d_4 (MaxPooling  (None, 12, 12, 256)      0
 2D)

 conv2d_7 (Conv2D)           (None, 12, 12, 384)       885120

 batch_normalization_7 (Batc  (None, 12, 12, 384)      1536
 hNormalization)

 conv2d_8 (Conv2D)           (None, 12, 12, 384)       1327488

 batch_normalization_8 (Batc  (None, 12, 12, 384)      1536
 hNormalization)

 conv2d_9 (Conv2D)           (None, 12, 12, 256)       884992

 batch_normalization_9 (Batc  (None, 12, 12, 256)      1024
 hNormalization)

 max_pooling2d_5 (MaxPooling  (None, 5, 5, 256)        0
 2D)

 flatten_1 (Flatten)         (None, 6400)              0

 dense_3 (Dense)             (None, 4096)              26218496

 dropout_2 (Dropout)         (None, 4096)              0

 dense_4 (Dense)             (None, 4096)              16781312

 dropout_3 (Dropout)         (None, 4096)              0

 dense_5 (Dense)             (None, 4)                 16388

=================================================================
Total params: 46,768,900
Trainable params: 46,766,148
Non-trainable params: 2,752
_________________________________________________________________
```

Fig. 2. AlexNet Model

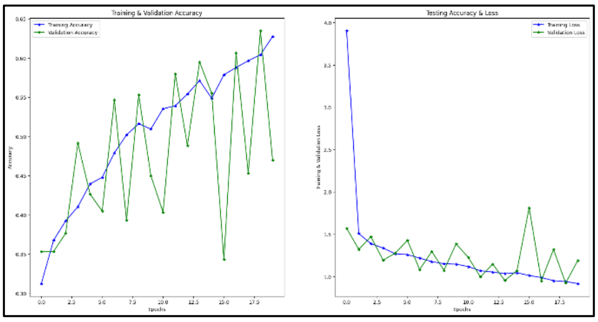

Fig. 3. AlexNet ACC and Loss Plot

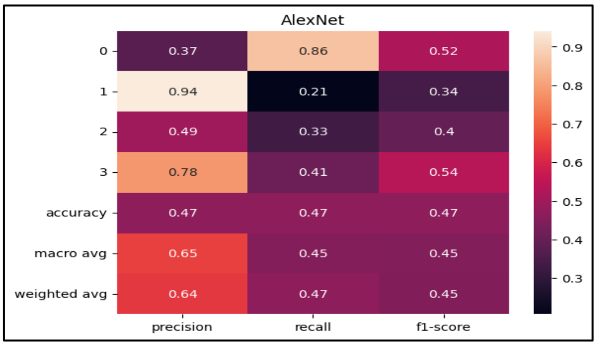

Fig. 4. AlexNet Parameters

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 vgg16 (Functional)          (None, 7, 7, 512)         14714688

 dropout_4 (Dropout)         (None, 7, 7, 512)         0

 flatten_2 (Flatten)         (None, 25088)             0

 batch_normalization_10 (Bat  (None, 25088)            100352
 chNormalization)

 dense_6 (Dense)             (None, 1024)              25691136

 batch_normalization_11 (Bat  (None, 1024)             4096
 chNormalization)

 activation (Activation)     (None, 1024)              0

 dropout_5 (Dropout)         (None, 1024)              0

 dense_7 (Dense)             (None, 512)               524800

 activation_1 (Activation)   (None, 512)               0

 dense_8 (Dense)             (None, 4)                 2052

=================================================================
Total params: 41,037,124
Trainable params: 26,270,212
Non-trainable params: 14,766,912
_________________________________________________________________
```

Fig. 5. VGG16 Model

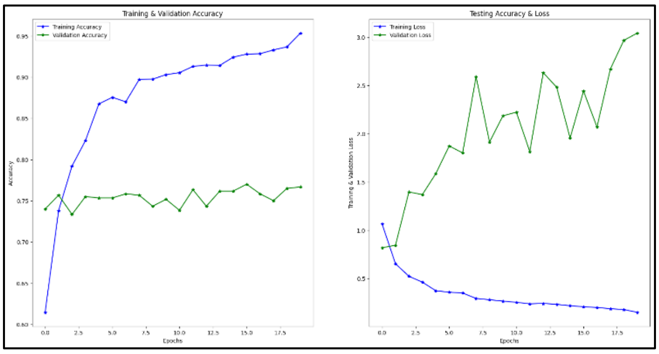

Fig. 6. VGG16 ACC and Loss Plot

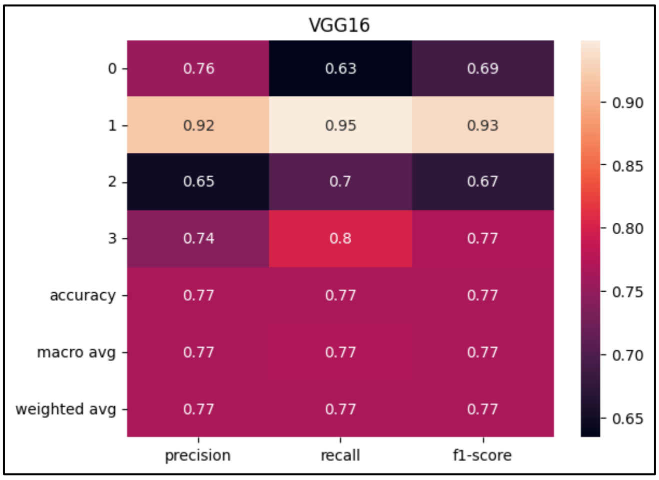

Fig. 7. VGG16 Paraameters

```
Model: "sequential_3"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 resnet50 (Functional)       (None, 7, 7, 2048)        23587712

 dropout_6 (Dropout)         (None, 7, 7, 2048)        0

 flatten_3 (Flatten)         (None, 100352)            0

 batch_normalization_12 (Bat  (None, 100352)           401408
 chNormalization)

 dense_9 (Dense)             (None, 2048)              205522944

 batch_normalization_13 (Bat  (None, 2048)             8192
 chNormalization)

 activation_2 (Activation)   (None, 2048)              0

 dropout_7 (Dropout)         (None, 2048)              0

 dense_10 (Dense)            (None, 1024)              2098176

 batch_normalization_14 (Bat  (None, 1024)             4096
 chNormalization)

 activation_3 (Activation)   (None, 1024)              0

 dropout_8 (Dropout)         (None, 1024)              0

 dense_11 (Dense)            (None, 4)                 4100

=================================================================
Total params: 231,626,628
Trainable params: 207,832,068
Non-trainable params: 23,794,560
_________________________________________________________________
```

Fig. 8. ResNet 50 Model

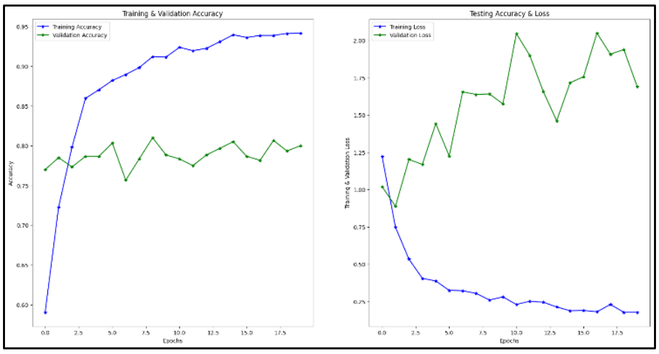

Fig. 9. ResNet 50 ACC and Loss Plot

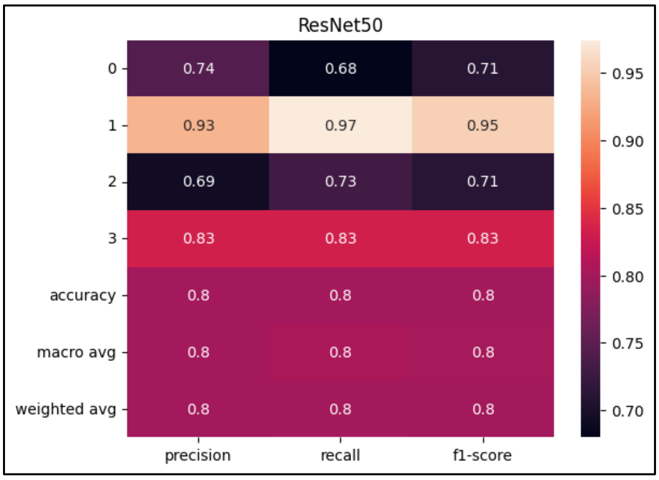

Fig. 10. ResNet 50 Parameters

```
Model: "sequential_4"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_10 (Conv2D)          (None, 223, 223, 64)      832

 max_pooling2d_6 (MaxPooling  (None, 111, 111, 64)     0
 2D)

 dropout_9 (Dropout)         (None, 111, 111, 64)      0

 conv2d_11 (Conv2D)          (None, 110, 110, 32)      8224

 max_pooling2d_7 (MaxPooling  (None, 55, 55, 32)       0
 2D)

 dropout_10 (Dropout)        (None, 55, 55, 32)        0

 flatten_4 (Flatten)         (None, 96800)             0

 dense_12 (Dense)            (None, 128)               12390528

 dropout_11 (Dropout)        (None, 128)               0

 dense_13 (Dense)            (None, 4)                 516

=================================================================
Total params: 12,400,100
Trainable params: 12,400,100
Non-trainable params: 0
_________________________________________________________________
```

Fig. 11. Proposed CNN Model

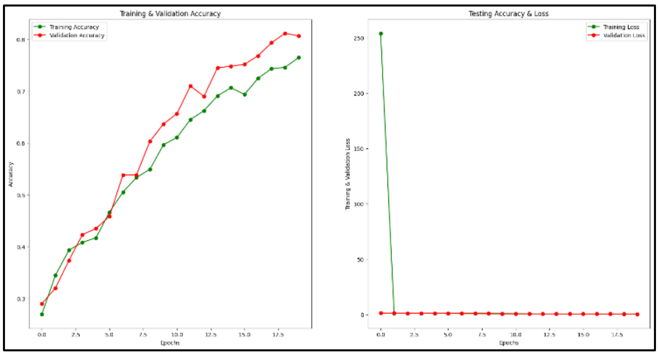

Fig. 12. Proposed CNN ACC and Loss Plot

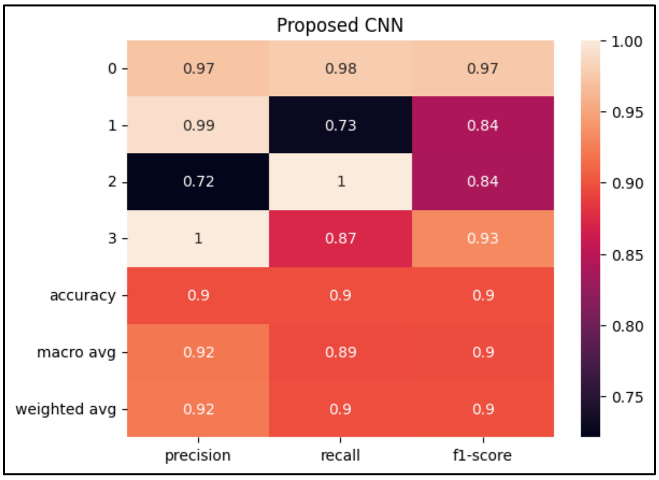

Fig. 13. Proposed CNN Parameters

TABLE I. TRANSFER LEARNING MODEL ANALYSIS

Model	Epoch	ACC (%)	P (%)	R (%)	F1-score (%)
AlexNet	20	47%	45%	45%	65%
Vgg16	20	77%	77%	77%	77%
ResNet50	20	80%	80%	80%	80%
Proposed CNN	20	90%	89%	92%	90%

CONCLUSION

In conclusion, the study presented a comprehensive analysis of various convolutional neural network (CNN) architectures, namely AlexNet, Vgg16, ResNet50, and a proposed CNN, for the classification of infected date palm leaves. Through rigorous experimentation over 20 epochs, the models were evaluated in terms of accuracy, precision, recall, and F1-score. The outcomes unveiled distinctive performance characteristics among the architectures. While AlexNet demonstrated moderate accuracy and precision at 47% and 45%, respectively, Vgg16 showcased balanced performance at 77% across all metrics. ResNet50 exhibited a consistent performance of 80% across all measures, indicating its robustness. Intriguingly, the proposed CNN emerged as the frontrunner, attaining an impressive 90% accuracy, 89% precision, 92% recall, and 90% F1-score. These findings underscore the efficacy of the proposed CNN in effectively identifying diverse infections in date palm leaves. The study not only contributes valuable insights to the field of automated disease detection but also highlights the potential for innovative architectural designs to yield substantial enhancements in accuracy. The remarkable performance of the proposed CNN showcases its adaptability to the complexities of the dataset. As such, this research significantly advances our understanding of leveraging deep learning architectures for the accurate identification of infected date palm leaves, offering pragmatic implications for agricultural sustainability and disease management practices.

REFERENCES

[1] M. Ahmed and A. Ahmed, "Palm tree disease detection and classification using residual network and transfer learning of inception ResNet," PLoS ONE, vol. 18, no. 3 March, pp. 1–19, 2023, doi: 10.1371/journal.pone.0282250.

[2] M. Shoaib et al., "An advanced deep learning models-based plant disease detection: A review of recent research," Frontiers in Plant Science, vol. 14, no. March, pp. 1–22, 2023, doi: 10.3389/fpls.2023.1158933.

[3] K. M. Hosny, W. M. El-Hady, F. M. Samy, E. Vrochidou, and G. A. Papakostas, "Multi-Class Classification of Plant Leaf Diseases Using Feature Fusion of Deep Convolutional Neural Network and Local Binary Pattern," IEEE Access, vol. 11, no. May, pp. 62307–62317, 2023, doi: 10.1109/ACCESS.2023.3286730.

[4] A. M. AL-Mahmood, H. I. Shahadi, and A. R. Hasoon Khayeat, "Image dataset of infected date palm leaves by dubas insects," Data in Brief, vol. 49, p. 109371, 2023, doi: 10.1016/j.dib.2023.109371.

[5] A. Hessane, A. El Youssefi, Y. Farhaoui, B. Aghoutane, and F. Amounas, "A Machine Learning Based Framework for a Stage-Wise Classification of Date Palm White Scale Disease," Big Data Mining and Analytics, vol. 6, no. 3, pp. 263–272, 2023, doi: 10.26599/BDMA.2022.9020022.

[6] K. Harshavardhan, P. J. V. A. Krishna, and A. Geetha, "Detection of Various Plant Leaf Diseases Using Deep Learning Techniques," in 2023 International Conference on Advances in Computing, Communication and Applied Informatics (ACCAI), 2023, pp. 1–6. doi: 10.1109/ACCAI58221.2023.10200031.

[7] N. Nafiiyah, N. S. Fatonah, R. Wardhani, B. Jokonowo, and T. A. Y. Siswa, "Majority voting transfer learning CNN for peanut leaf types identification," in 2022 3rd International Conference on Electrical Engineering and Informatics (ICon EEI), 2022, pp. 70–74. doi: 10.1109/IConEEI55709.2022.9972271.

[8] Z. Wu, F. Jiang, and R. Cao, "Research on recognition method of leaf diseases of woody fruit plants based on transfer learning," Scientific

Reports, vol. 12, no. 1, pp. 1–9, 2022, doi: 10.1038/s41598-022-18337-y.

[9] A. M. Al-Mahmood, H. I. Shahadi, and A. R. H. Khayeat, "Classifying Infected Palms with Dubas's Bug Based on Artificial Intelligence," in 2022 International Conference on Electrical, Computer and Energy Technologies (ICECET), 2022, pp. 1–6. doi: 10.1109/ICECET55527.2022.9872955.

[10] A. Hessane, A. E. Youssefi, Y. Farhaoui, and B. Aghoutane, "Toward a Stage-wise Classification of Date Palm White Scale Disease using Features Extraction and Machine Learning Techniques," in 2022 International Conference on Intelligent Systems and Computer Vision (ISCV), 2022, pp. 1–6. doi: 10.1109/ISCV54655.2022.9806134.

[11] Ü. Atila, M. Uçar, K. Akyol, and E. Uçar, "Plant leaf disease classification using EfficientNet deep learning model," Ecological Informatics, vol. 61, p. 101182, 2021, doi: https://doi.org/10.1016/j.ecoinf.2020.101182.

[12] J. Gu, P. Yu, X. Lu, and W. Ding, "Leaf species recognition based on VGG16 networks and transfer learning," in 2021 IEEE 5th Advanced Information Technology, Electronic and Automation Control Conference (IAEAC), 2021, vol. 5, pp. 2189–2193. doi: 10.1109/IAEAC50856.2021.9390789.

[13] H. Alaa, K. Waleed, M. Samir, M. Tarek, H. Sobeah, and M. A. Salam, "An intelligent approach for detecting palm trees diseases using image processing and machine learning," International Journal of Advanced Computer Science and Applications, vol. 11, no. 7, pp. 434–441, 2020, doi: 10.14569/IJACSA.2020.0110757.

[14] R. Nishad and T. A. Ahmed, "Survey and identification of date palm pathogens and indigenous biocontrol agents," Plant Disease, vol. 104, no. 9, pp. 2498–2508, 2020, doi: 10.1094/PDIS-12-19-2556-RE.

[15] A. Magsi, J. A. Mahar, M. A. Razzaq, and S. H. Gill, "Date Palm Disease Identification Using Features Extraction and Deep Learning Approach," in 2020 IEEE 23rd International Multitopic Conference (INMIC), 2020, pp. 1–6. doi: 10.1109/INMIC50486.2020.9318158.

[16] K. J. Alwahshi et al., "Molecular identification and disease management of date palm sudden decline syndrome in the united arab emirates," International Journal of Molecular Sciences, vol. 20, no. 4, 2019, doi: 10.3390/ijms20040923.