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Deep Learning Technique for Early Diagnosis of Date Palm Pests: A Review

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Abstract: Date palm trees, a crop of immense cultural and economic significance in the Middle East, are seriously threatened by insect pests. These pests inflict substantial damage on tree health and fruit yields, with infestations often progressing undetected until irreversible harm has occurred. The urgency of this issue is magnified by FAO estimates attributing 20-40% of global food loss to plant pests and diseases, highlighting an acute need for advanced detection methodologies. This review paper combines current research on the use of deep learning-based convolutional neural networks (CNNs) to automatically identify and classify palm tree pests using image analysis. The paper examines how a model of CNN models, trained on a variety of datasets of leaf imagery, demonstrates exceptional effectiveness in monitoring early and precise indicators of infection, such as leaf wilting, discoloration, and deformation. By combining these systems, farmers can manage pests in a revolutionary way and acquire the skills to respond accurately and in real time. With increasing demand for food and environmental concerns, this technological revolution is essential to improve crop resilience, ensure high productivity, and promote sustainable farming practices.

Keywords: Pest Detection, Classification, Date Palm, Deep Learning.

Introduction

In the Middle East, palm trees play a central role as a fundamental crop of significant cultural and economic relevance. However, it is frequently infested by several harmful insects. The red palm weevil, which has caused extensive destruction in the Gulf countries since the 1980s, is one of the most dangerous pests (Ahmed & Ahmed, 2023) .

According to the Food and Agriculture Organization (FAO), 20% and 40% annual crop losses are directly caused by insects and diseases, respectively, highlighting the need to combat these pests on a global scale. This draws attention to a serious weakness in food security. The severe limitations of traditional detection techniques exacerbate this problem, as visual examination of internal damage caused by the weevil, which is often hidden, is ineffective, prone to error, and unsuitable for early management (Pacal *et al.*, 2024). Therefore, the urgent need to investigate sophisticated issues and try to find automated solutions is the driving force behind this article, which clearly assesses how deep learning models can provide a revolutionary way to detect and manage pests at an early stage accurately.

Additionally, Dubas bugs (Ommatissus lybicus) pose another major threat, especially to date palms (Phoenix dactylifera). These small pests live on the leaves of palm trees and feed themselves by digging holes, which leads to dryness and deformation of leaves. In places where the Dubas bug insect is severely affected, it can adversely affect the general health of palms, reducing the fruit production (Nobel *et al.*, 2024) .

Image processing technology, specifically designed for palm pest identification, significantly improves the efficiency of agricultural operations. These models enable farmers to focus on other important aspects of farming by drastically reducing human effort. Real-time detection tools allow farmers to take immediate action before the infestation spreads and severely impacts the crop. Early diagnosis is crucial for minimizing damage and boosting overall palm production (Magsi *et al.*, 2023).

This study demonstrates how convolutional neural networks (CNNs) can be considered as a valuable tool for diagnosing palm tree problems. The CNN model was used to analyze and classify images, which had assisted in diagnosing numerous diseases (Hu *et al*., 2025). In the application, the network is trained and tested using image databases, which enables it to recognize disease features by analyzing visual symptoms, such as leaf discoloration, shedding, wilting, or spotting. As a result, CNN has helped build a strong decision-making model that allows farmers to detect diseases at an early stage, thereby promoting higher agricultural productivity and crop quality. This technology has proven to represent a shift toward a more advanced and effective agricultural model (Magsi *et al.*, 2020).

Materials & Methods

Common Pests and Diseases

Pests and diseases that damage date palm leaves are divided into the following categories:

Bugs

Palm trees are severely damaged by Bug infestations, which negatively affect their productivity and general health. In addition to the leaves, fruit, and woody tissue of the palm, these insects consume the sap as well as other elements of the palm. In addition, certain insects can spread pathogens, which raises the probability of contracting a disease (Gitau *et al.*, 2009).

Ommatissus lybicus (Dubas)

The date palm Ommatissus lybicus has been identified as a pest that negatively affects date palm trees, causing direct damage as a result of its feeding on the palm tree, in addition to indirect damage resulting from the secretion of honeydew, which leads to increased mold growth on the trees(Al Shidi et al., 2018).

Leaf spot

Leaf spot is a fungal disease impacting date palm trees. Mycosphaerella tassiana causes disease in date palm leaves. The disease spreads through the air and can also be transmitted via infected offshoots. Symptoms include distinct dark spots on green leaves, and when the leaves die, the edges of the spots remain reddish-brown while the center turns pale. Spots can also occur on the rachis and spines. The bacterial leaf blight is mostly represented by brown to black regions that extend outward and cause ulcers to grow on the leaf's midrib (Saxena *et al.*, 2020). Alternatively, the brown spot disease impacts the leaves and spines, which is revealed by the formation of ill-defined dark spots with pale centers and brown-to-gray borders.

Fig. (1) illustrates the different types of pests and diseases affecting palm leaves.

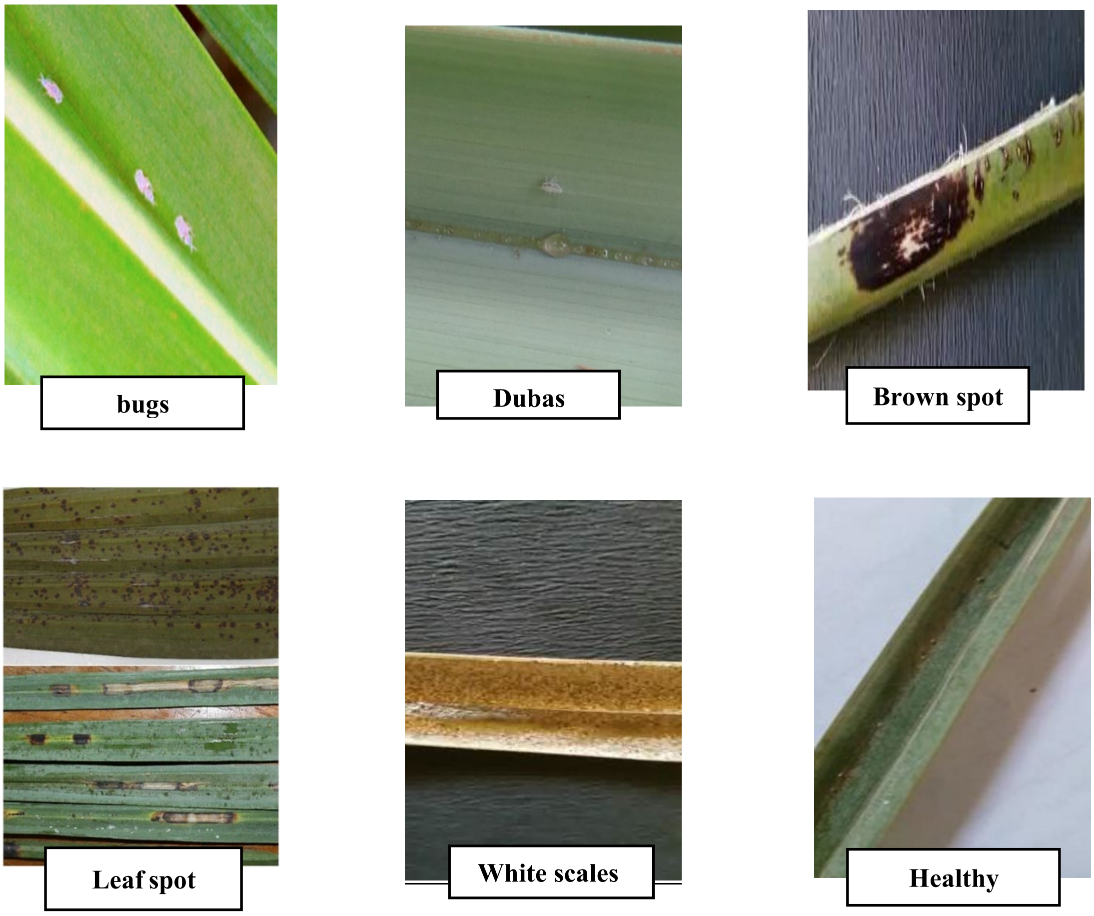

Fig. (1): The different types of pests and diseases affecting palm leaves.

Related Work

Agriculture is an important part of any economic system that contributes to the gross domestic product and needs support to increase productivity through the adoption of modern technologies (Liu & Li, 2025). Diseases and pests cause large losses in date palm production. Rapid identification and diagnosis of these pests and diseases is therefore essential to maintaining palm health, preserving crops, and enhancing production (Mohammed & Munir, 2024).

Numerous researchers' studies addressed a wide range of issues, from developing new models to improving current ones through the use of strategies like transfer learning.

Table (1) summarizes the details of each study, including the article title, objectives, sample size, algorithms or techniques, and limitations.

Methodological Overview

This section summarizes the methodology used in previous research to identify palm leaf disease using CNNs. The following subsections explain the model structure, evaluation criteria, and model data division techniques discussed in the literature.

Table (1): Summary of Related Works on Modern Technologies-Based Plant and Date Palm Disease Detection.

#	Article Title	Objectives	Sample Size	Algorithms	Limitations	Strengths	Weaknesses
(Mohammed, K., et al., 2024)	Classification of Palm Tree Diseases Using Convolutional Neural Networks	Apply CNNs to classify palm diseases from leaf images.	~200–300 images (estimated)	Custom CNN	The dataset is small, there is no public code or data, and there are limited disease classes.	Specific focus on palm tree diseases, which is a targeted application.	Very small dataset; lack of reproducibility (no public code/data); limited scope of diseases.
Abu-) zanona *et* (*al*., 2022	Plant Disease Diagnosis and Image Classification Using Deep Learning	Develop DL models for general plant disease detection.	PlantVillage + custom datasets (~50k images)	ResNet, VGG, custom CNN	Focus is not specific to date palms; real-field validation is limited.	Large and diverse dataset; use of established, powerful models.	Not specific to date palms; lacks validation in real-world field conditions.
Sharma) *et al*., (2022	Detection of plant leaf diseases using deep convolutional neural network models	Compare CNN architectures for leaf disease detection.	PlantVillage (~54k images)	VGG16, ResNet50, DenseNet, custom CNN	The product was tested on common crops (tomato, apple), not date palms.	Comprehensive comparison of multiple modern CNN architectures.	Findings are not directly applicable to date palms, as they were tested on different crops.
Singla *et*) (*al*., 2024	Deep learning models for plant disease detection and diagnosis	Evaluate CNNs for plant disease classification across species.	PlantVillage (~54k images)	AlexNet, GoogLeNet, custom CNNs	The images are lab-controlled and have poor generalization to real-world field conditions.	Broad evaluation across multiple plant species.	Models trained on lab-controlled images may not perform well in realistic agricultural settings.
Ferentino) (s, 2018	Fundamentals of Artificial Neural Networks and Deep Learning	Explain ANN/DL foundations for genomic and agricultural applications.	Theoretical	N/A (tutorial)	This is not an empirical study; there are no disease detection results.	Provides foundational theoretical knowledge for the domain.	Not applicable for practical disease detection; no empirical results or models.
Montesin) os López et al., (2022	An advanced deep learning model-based plant disease detection: A review	Review recent DL approaches for plant disease detection.	N/A (review)	Survey of CNNs, Transformers, etc.	There were no original experiments, and the date palm coverage was minimal.	Provides a broad overview of the latest trends and models in the field.	No original research; minimal specific information on date palm diseases.
Shoaib et) (al., 2023	A Survey on Deep Learning: Algorithms, Techniques,	Broad survey of DL across domains.	N/A	Overview of CNNs, RNNs, GANs, etc.	The focus is not on agriculture or plant disease.	Very wide scope, covering deep learning fundamentals	Irrelevant to the specific problem of plant or date palm disease detection.

	and Applications					and various applications.	
Pouyanfa) r *et al*., (2018	Plant Leaf Disease Detection by Deep Learning: A Literature Review	Review DL-based leaf disease detection methods.	N/A (review)	CNNs, hybrid models	General review; limited focus on palms or fruit trees.	Summarizes a wide range of methods specifically for leaf disease detection.	Lacks a specific focus on palm trees or date palms.
Das *et*) (*al*., 2024	A Deep Learning-Based Model for Date Fruit Classification	Classify date fruit varieties/quality using DL.	~1,500 date fruit images	MobileNetV2, ResNet	Focuses on fruit."	Directly relevant to the date palm agricultural chain (post-harvest).	The focus is on fruit quality/variety, not on leaf or tree diseases.
Albarrak) *et al*., (2022	DPXception: a lightweight CNN for image-based date palm species classification	Classify date palm species (not diseases) using a lightweight CNN.	~2,000 palm images	Custom lightweight CNN (DPXception)	Targets species identification."	Specific to date palms, it proposes an efficient, lightweight model suitable for mobile deployment.	Addresses species classification, not disease detection, which is a different problem.

This survey approach uses models of convolutional neural networks (CNN) to classify images accurately and efficiently. A sequential model was utilized to make the neural network establishment process easier, and the model was constructed using the Keras toolkit (Hua, 2024). With a particular percentage of images used for training and others for testing, the data is split into groups for data training and data testing (Sharma *et al.*, 2022).

Data Partitioning

Typically, the dataset is split into two main categories (Singla *et al.*, 2024). The training dataset, which contains the majority of the data, is about 80% used by the model for training. This allows the model to learn from the characteristics and patterns found in the training dataset and the testing dataset, which is a smaller part of the data (around 20%), designed specifically to assess the model's efficiency in classifying new invisible data that was not addressed during the training phase.

Model Construction

To create a model that uses deep neural networks to classify palm leaf pests, especially those that infect them, it is necessary to provide a comprehensive explanation of the structure of the model. These decisions are influenced by the data provided, including the size of the image, the number of target groups, the frequency of disease patterns, and the complexity of the classification method (Ferentinos, 2018).

This model begins with an input layer that receives a digital image of palm leaves, and is used as an entry point to the network. With many neurons exactly matching the dimensions of the image, the main task of this layer is to introduce the pixel density value into the network model. Ensure dimensional coherence of the following layers (Montesinos López *et al.*, 2022).

Following the input layer, the hidden layers provide a full explanation of the structure of the model; these layers are used to create systems that rely on deep neural networks to classify plant leaf pests, especially those that infect palm leaves. This process involves determining the quantity, types, and arrangement of layers as well as their interactions inside the network. The properties of the data provided, including the dimensions of the image, the number of target categories, the spread of pest patterns, and the complexity of the classification function in general, affect these options. Excessive abundance of layers may lead to unnecessary complexity, affecting performance adversely. To achieve optimal performance in a network, precise design of hidden layers is needed Shoaib *et al.*, 2023).

Finally, in deep neural networks (DNNs), processed data that reaches the output layer is essential in determining model results. This layer generates output using properties derived from previous levels. There are two main types of layers: the linear layer, which predicts the numerical value in regression, and the other type that defines the task (classification or regression) and improves the performance of the model by choosing the appropriate activation function to increase the accuracy of the results.

The SoftMax layer is used for multi-class classification and converts the results into probabilities that sum to one (Pouyanfar *et al.*, 2019). Other layers, like the Pooling and Dropout layers, first aim to lower the total number of dimensions of the image dataset by minimizing the parameters required and enhancing the neural network's efficiency. This approach speeds up data processing and reduces the risk of overfitting. There are two key kinds of pooling: (Max) Pooling, which selects the highest value in each region, helping to retain the most significant features of the data, and (Average) Pooling, which computes the average value inside the region. While average pooling is the least common, it may cause the loss of some important features (Das *et al.*, 2024); the latter is believed to be a successful strategy to avoid overfitting of neural networks. This layer randomly removes a certain percentage of neurons throughout the training process. Since the probability of leakage is limited to 0.5 in this case, half of the neurons are removed with each update of the model. By enhancing the model's ability to learn more patterns, this technical support prevents it from relying excessively on specific features (Albarrak et al., 2022). The SoftMax activation function is used in the last layer to provide a vector that describes the distribution of probability between different output classes. This structured approach to the CNN model allows images to be efficiently learned and classified using the characteristics it has collected from its different layers (Sharma *et al.*, 2022; Singla *et al.*, 2024).

The model learns how to recognize patterns and attributes associated with plant diseases using a range of images from different places, including field and laboratory images. This can be achieved through multiple training periods, which include displaying the dataset on the trained model multiple times, and in each epoch, it further improves the feature detection accuracy. As the number of epochs increases, the model's capability to adapt and learn from the data improves (Ferentinos, 2018).

Evaluation Measurements

To detect images of palm pests, model evaluation is essential. This section covers multi-category classification tasks using the deep learning framework. F1-score, recall, accuracy, precision, and examples of common evaluation measures. Each prediction has four possible outcomes, taken from the confusion matrix (Farhadpour *et al.*, 2024).

- True Positives -TP-: rightly identified positives.
- True Negatives -TN-: rightly identified negative results.
- False Positives -FP-: negatives wrongly predicted as positives.
- False Negatives -FN-: positives wrongly predicted as negatives.

To compare the performance of models, a series of core metrics was used on various datasets. These standards include (Safran *et al*., 2023):

Accuracy

Accuracy is a commonly used global metric, especially when three or more instances of class M are involved. It represents the ratio of correctly predicted cases to the total number of cases in the dataset. It is calculated by Eq. (1).

$$Acc = \frac{TP+TN}{TP+FN+FP+TN} \quad \text{….. (1)}$$

Precision

Precision measures how accurately the model identifies positive cases. Precision calculates the proportion of correctly predicted positive cases among all positive predictions. It reflects the reliability of positive classifications. It is calculated by Eq. (2).

$$Prec = \frac{TP}{TP+FP} \quad \text{….. (2)}$$

Recall

Recall (sensitivity) measures the proportion of actual positive cases (e.g., diagnosed individuals) correctly identified. It is calculated as the ratio of true positives to the sum of true positives and false negatives, as mentioned in Eq. (3).

$$Recall = \frac{TP}{TP+FN} \quad \text{….. (3)}$$

F1-Score

Unlike accuracy, which represents overall performance, F1 Score evaluates the predictive ability of the model by balancing two important measures: accuracy and recall. It is widely used in recent literature for its effectiveness in handling imbalanced datasets. It is calculated by Eq. (4).

$$F1-score = \frac{Prec*Recall}{Prec+Recall} \quad \text{….. (4)}$$

Detection and Classification

Lately, there has been a rise in the use of machine learning techniques that focus on classifying palm leaf pests as an active tool. This consists of four major stages:

Preprocessing

Preprocessing is the first stage, which involves frequent use of raw data and has difficulty achieving high accuracy when used with classification techniques. Various pre-processing methods are used to improve model performance. One such method is to normalize the average, which produces a more consistent representation of brightness across the dataset by calculating the average of each feature in the data and subtracting this mean from each image. Another important method is standardization, which depends on dividing the average through calculation. Through its feature, this procedure improves compression by converting data into one standard deviation and an average equal to zero. As well, Zero Component Analysis (ZCA) plays an essential role in the advancement of edge vision of images, which is extremely important for effective feature detection by models. ZCA begins with normalization of size, followed by mean normalization, and includes counting the singular value analyses of the variation matrix before applying whitening (Pal & Sudeep, 2016).

Feature Extraction

Feature extraction, an examination of traits that includes color, shape, surface texture, and other similar attributes, is part of the second stage. The overall efficacy and image quality of data palm leaves are evaluated using trait extraction. There are several ways to determine the properties of pests that harm date palm leaves, including (i) global color histogram, which helps detect any color shift that can indicate the presence of a pest by analyzing the distribution of colors in the image of the palm leaf, and (ii) local color histogram, which involves dividing the image into local M*N blocks. This technique uses local histograms to facilitate image analysis. After recovering the feature for each block, pattern similarity metrics are calculated by focusing on particular regions rather than examining the entire picture at once (Ahmed et al., 2021). (iii) The LBP (local binary pattern) describes the texture of a small region of a palm leaf and may represent changes caused by fungi. An improved LBP called Complete LBP considers all available data, enhancing the accuracy of texture description and the system's capacity to identify pests *(Jamjoom et al*., 2023)

Detection

The detection stage is one of the most important stages in the date palm pests' life cycle. The most important methods used in the detection or classification of date palm pests are listed in the following subsections:

ResNet

ResNet is an advanced deep learning network designed for the classification and identification of pests in palm leaves. This network may solve the problems of fading gradients and weaknesses faced by deep network models due to several nonlinear layers. In deep learning, stacking many classes often leads to learning important identity tasks. A prominent feature of the ResNet network is its innovative use of residual connections, which improves the network's ability to learn identity relationships effectively. By enabling networks to remain trained during deepening, this technique successfully addresses the problem of gradual fading. There are many overloaded units in each of the remaining blocks in the structure. These modules facilitate the smooth flow of gradients through backpropagation, or reverse propagation, which promotes the successful training of a deep neural network. Furthermore, ResNet uses 3x3 filters, which empower it to pick up complex patterns inside the data. The entered images are uniformly sized at 224×224 pixels, ensuring uniformity in processing and letting the network efficiently analyze plant leaf images for pest detection tasks (Hukkeri *et al.*, 2024). Fig. (2) outlines the typical architecture of ResNet.

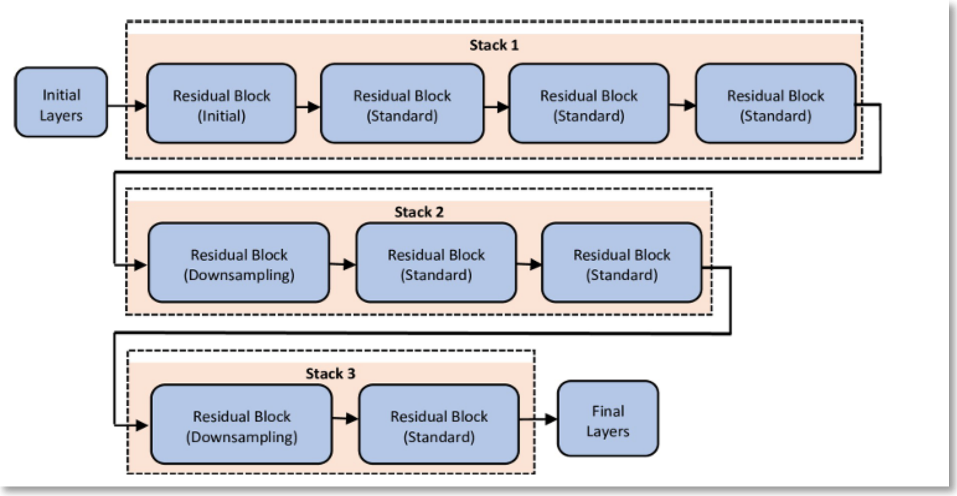

Fig. (2): Architecture of ResNet.

VGG16 and VGG19

As seen in Fig. (3), Simonyan and Zisserman created a popular model in the field of convolutional neural networks in 2014. This is due to the presence of many more convolutional layers, unlike the topology of other models such as AlexNet and SqueezeNet. During the analysis of images, VGGNet showed an outstanding performance in identifying plant pests (Theerthagiri *et al.*, 2024). This architecture is composed of 13 convolutional layers followed by 5 (max) pooling layers. Each convolutional layer, depending on its depth, contains between 64 and 512 filters. The structure's final layers, similar to those used in AlexNe, consist of two dense layers containing 1000 neurons. In general, both VGG16 and VGG19 are powerful models of deep learning, making them ideal tools for tasks such as plant pest diagnosis (Malpe, 2019).

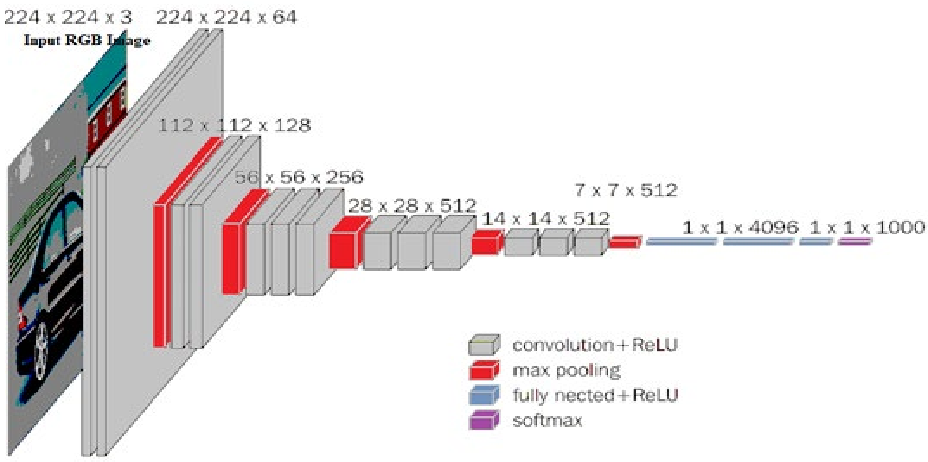

Fig. (3): Architecture of VGG16.

Dense Net

Dense Net (Densely Connected Convolutional Networks) is a sophisticated neural network architecture designed to facilitate the transmission of information across layers. Each layer can benefit from the maps of features extracted from all previous layers, as this model describes the direct links between each layer. This structure helps improve the accuracy of the model and increases the network's ability to learn (Chilakalapudi & Jayachandran, 2024).

Fig. (4) shows the architecture of DenseNet. To ensure continued availability between the layers, each dense block is connected to each previous block using the feedforward method, which improves network data flow and gives more accurate results.

U-Net

U-Net, a twisted neural network structure, is a common model of image segmentation. What distinguishes this structure is its symmetrical U-shaped structure, which seamlessly blends an extended path (decoder) and a shrinking path(encoder). The encoder, typical of CNNs, gradually decreases the spatial dimensions of the input image via a sequence of convolutional and pooling layers, gathering contextual information and determining "what" features are there. The decoder then reverses the process, using transposed convolutions to unsampled the feature maps and recover spatial information to determine "where" the features are.

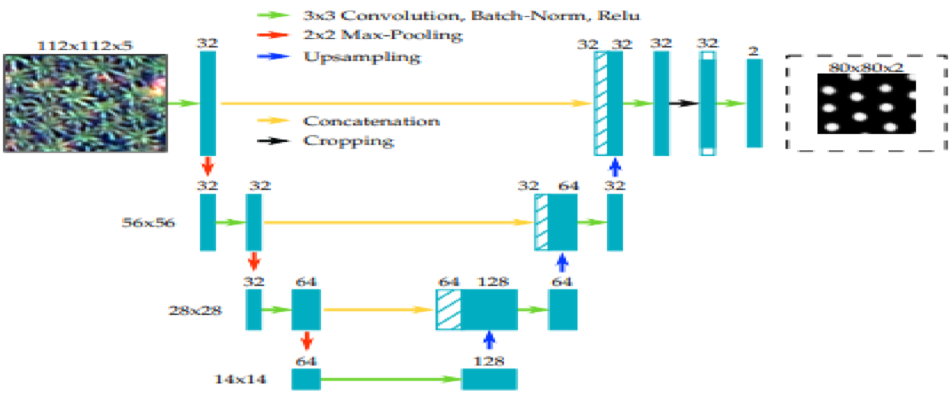

Fig. (4): Architecture of DenseNet.

As a result, U-Net excels at producing highly exact, pixel-by-pixel segmentations even with limited training data, making it especially useful for jobs requiring accurate object delineation and border identification. Fig. (5) depicts the famous U-shaped architecture, emphasizing the contracting path, bottleneck, expanded path, and critical skip connections (Alemi *et al.*, 2020).

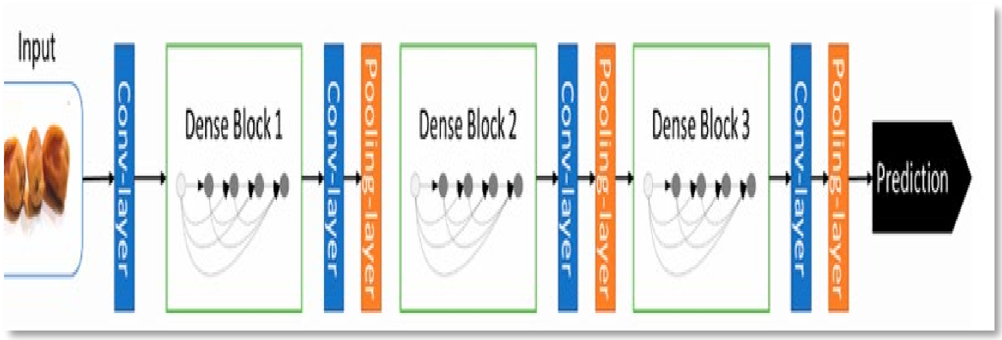

Fig. (5): Architecture of U-Net.

Classification

There are several different approaches that help accurately identify and classify plant diseases. This section provides a summary of a number of known methods.

Interactive Segmentation, through user input, this image processing technology determines the boundaries of elements within the image. The user can draw lines or place points around the target elements to identify specific areas. Algorithms are used to divide elements and evaluate the image to improve the accuracy of recognition. Applications such as image and medical diagnosis can benefit from this technology. When combined with human communication, they give accurate and reliable results (Barbedo & Garcia, 2013).

Fuzzy logic ,is a mathematical technique that simulates the traditional approach, based on fixed values (true or false), to address uncertainty and inaccurate information in the fuzzy logic supports degrees of truth, making it suitable for a range of applications that include the processing of images of palm trees in cases where visual data may be blurred or incomplete, this flexibility allows for more precise decisions and analysis (Dandawate & Kokare, 2015).

Decision support machines (DSM) are a way to help farmers make thoughtful decisions about crop management. To provide accurate advice on plant health, the DSM relied on data analysis, which increased the effectiveness of decision-making. DSM aims to increase agricultural production and bridge the technological gap between farmers and scientific research(Rupnik *et al.*, 2019).

Eigenfeatures, are extracted features from data that are used for image analysis and pattern recognition. They came from variance analysis and are based on scatter matrices. Self-traits are needed for categorized images by discriminating between multiple organisms, such as healthy and infested leaves (Qadri et al., 2024).

The K-means clustering, method is a data classification model that uses specific patterns to separate items into K groups. Assign each pixel to the nearest group after selecting random centers for each category. The average of the given pixel coordinates is used to calculate the center of the group. This process continues unit the positions of the group stabilize (Gülmez, 2025).

Edge detection, this method makes it possible to identify a variety of pests, including Fusarium withering in cotton leaves (Javidan *et al.*, 2023).

Neural Network-Based Techniques, these techniques demonstrate excellent accuracy in identifying pests using information from each pixel, making them suitable in a variety of situations (Bairwa et al., 2024) .

Deep learning techniques, by analyzing leaf images and identifying key characteristics, including shape, color, and texture, deep learning techniques are frequently used to classify plant leaf pests, especially palm pests. 94% accuracy has been achieved (Singh *et al.*, 2020).

Color transformation techniques, in order to reduce background noise, use color models such as YCbCr and CIELAB, which help minimize background noise (Mengistu et al., 2018).

Decision trees, decision trees help classify pests and simplify the process by collecting data on plant pest symptoms and setting rules specific to each symptom. Excavation rules are used in the decision tree when specific symptoms appear unit the final diagnosis is made. This method improved the reliability of the results by directing the machine towards accurate classification of the lesions based on the symptoms introduced (B. Rajesh *et al.*, 2020).

Support Vector Machines, (SVM) is a model used to classify the retrieved features into several groups. After extracting the feature, these features are employed to select whether some pests have damaged the palm leaves (Alsirhani *et al.*, 2023).

Techniques for the diagnosis of pests and diseases of resident plants show a clear shift from manual processes to automated artificial intelligence systems. Accuracy is achieved through interactive segmentation, but it is not scalable and requires direct human intervention. Although they rely on hand-made parameters that restrict their ability to adapt, traditional computer vision methods, such as K-means clustering, edge detection, and color transformation, allow them to be automatically extracted.

Rule-based systems, like decision trees and fuzzy logic, give interpretable decision routes but require substantial specialist knowledge to create and maintain. Statistical classifiers like support vector machines provide robust pattern identification but remain dependent on quality feature engineering.

Through the self-extraction of vital information from images, contemporary deep learning algorithms have made remarkable progress in accurately diagnosing diseases with minimal human intervention. History shows the necessity of interpretability and self-performance. Recent studies support deep learning systems due to their scalability and effectiveness in handling data using complex visual input.

Conclusion

Through an inclusive overview of the academic literature on discovering and classifying palm leaf pests, several major results can be drawn that reflect both the advances made in this field and the remaining challenges. The overall conclusion of this review is that the accuracy of the classification and detection model is not based solely on a single template or network. Alternatively, it is based on a sequence of processes consisting of multiple relative stages, beginning with preprocessing the dataset, followed by extraction, and finishing with selection of the correct model for classification or detection.

Image-based classification systems, especially in agricultural environments, begin with pretreatment processes. Contrasts in lighting, variations, and background noise are common in images taken in normal settings, reducing the quality of representation of the displayed data. Several methods or networks are used, like

Mean normalization concentrates the values of pixels about zero and helps promote learning stabilization by decreasing unnecessary variation between images.

Standardization, which rescales the number of features to have a zero mean and one variance, easily improves pattern recognition in the model.

ZCA Whitening resets a range of properties to have a one contrast and a zero average, making it easier for the system to acknowledge patterns.

These preprocessing techniques significantly increase the model's ability to learn from image input, resulting in more accurate and reliable results.

To convert unprocessed image data into an understandable semantic representation of a classification system, the extraction of attributes is essential after preprocessing. Important features consist of the following:

Tissue patterns, such as Local Binary Patterns (LBP) and complete LBP, are useful in detecting subtle structural changes caused by fungal infection or insect damage. These features increase the accuracy of the classification, allowing for a more precise distinction between healthy and diseased leaves.

According to the study, deep learning models such as DenseNet, ResNet, VGG, and U-Net were necessary to achieve high performance.

The review includes different classification methods, like using a deep learning network, or classical techniques such as k-means algorithms, while others relied on division roles. This option is best suited to specific data types and operating settings. The importance of integrating multiple techniques preprocessing, feature extraction, and an advanced classification model, is a key finding of the review.

Systems that rely solely on raw images without proper preprocessing or feature extraction tend to underperform and lack robustness in real-world applications. Integrating these components results in more reliable and accurate automated detection systems.

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Contributions of Authors

M. A. M.: Sample collection, Laboratory methodology, and writing the manuscript.
A.H.H.: Suggested the proposal of the article, revised the manuscript.

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Conflicts of interest

The authors declare that they have no conflicts of interest.

Ethical approval

All ethical guidelines related to images issued by national and international organizations were implemented in this report.

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تقنية التعلم العميق للتشخيص المبكر لآفات نخيل التمر

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المستخلص: تتمتع أشجار النخيل بأهمية ثقافية واقتصادية كبيرة في الشرق الأوسط، حيث توفر محصولًا زراعياً مهماً ومصدراً للدخل للكثير من الناس. وتهدد الآفات مثل (Bug Dubas *Ommatissus lybicus* وسوسة النخيل الحمراء مخرجاتها، مما يتسبب في أضرار جسيمة لثمار النخيل وصحتها. عادة ما يكون من الصعب اكتشاف هذه الآفات من بين الإصابات الأخرى، مما قد يؤدي إلى تأخير أو اتخاذ تدابير علاجية غير صحيحة وإلحاق أضرار جسيمة بالمحاصيل. وبناء على ذلك، تشير تقديرات منظمة الأغذية والزراعة (الفاو) إلى أن الحشرات والأمراض تسبب ما بين 20 إلى 40% من فقدان الغذاء على مستوى العالم، مما يسلط الضوء على الحاجة الماسة إلى تدابير فعالة للإدارة والكشف. تركز هذه الدراسة على استخدام الشبكات العصبية التلافيفية للتعلم العميق (CNNs) في تحليل وتصنيف الأمراض التي تصيب أوراق شجرة النخيل باستخدام مجموعة من البيانات الصورية. عبر مجموعة التدريب على قواعد بيانات الصور، يحدد نموذج CNN مجموعة من الأعراض، مثل التشوه، تغير اللون، وذبول الأوراق، مما يسمح بالتشخيص الدقيق والمبكر. ويعزز النموذج المقترح قدرة المزارعين على الاختيار الصحيح ويساعد على تحسين جودة المحاصيل ورفع التدريبات الزراعية المثمرة والأكثر استدامة في مواجهة الطلب المتزايد على الغذاء والتحديات البيئية.

الكلمات المفتاحية: كشف الآفات، التصنيف، أشجار النخيل، التعلم العميق.