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Date Palm Disease Detection Using Inception V3 and VGG-16 Deep Learning Models

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Abstract—Date palm (Phoenix dactylifera) is a significant agricultural crop, but its productivity is often hampered by various diseases such as brown spot and white scale infestations. Early detection of these diseases is crucial for effective management and mitigation strategies. In this study, we propose a robust framework for date palm disease detection using deep neural network algorithms. The dataset comprising images of healthy date palms, brown spot affected palms, and white scale infested palms is obtained from Kaggle. Prior to model training, the images undergo preprocessing techniques, including median filtering, to enhance their quality and reduce noise. Features are then extracted from the preprocessed images. Two state-of-the-art deep learning models, namely Convolutional Neural Network (CNN) Inception V3 and VGG-16, are employed for disease classification. The performance of each model is evaluated using test loss and test accuracy metrics. Our experimental results demonstrate promising performance, with CNN achieving a test loss of 1.29 and a test accuracy of 0.33, Inception V3 achieving a test loss of 0.087 and a test accuracy of 0.93, and VGG-16 achieving a test loss of 0.049 and a test accuracy of 0.98. The comparative analysis reveals that VGG-16 outperforms the other models in terms of both accuracy and loss metrics, indicating its efficacy for date palm disease detection tasks. Overall, this study showcases the potential of deep neural networks in automated and accurate diagnosis of date palm diseases, thereby facilitating timely interventions and enhancing crop yield..

Keywords—Date palm disease detection, Deep neural networks, CNN Inception V3, VGG-16, Image pre-processing, Feature extraction, Brown spot, White scale etc.,

I. INTRODUCTION

Date palm (Phoenix dactylifera) is a crucial agricultural crop cultivated in various regions worldwide, contributing significantly to food security and economic sustainability in many communities. However, the productivity and health of date palm trees are often threatened by various diseases and pests, leading to substantial yield losses if left unmanaged. Among the most common diseases affecting date palms are brown spot and white scale infestations, which can severely impact both the quantity and quality of the date fruit harvest.

Early detection and accurate diagnosis of these diseases are imperative for implementing timely and effective management strategies to mitigate their spread and minimize crop losses. Traditionally, disease diagnosis has relied on visual inspection by agricultural experts, which can be time-consuming, subjective, and prone to errors. Therefore, there is a growing need for automated and reliable methods for detecting and diagnosing date palm diseases.

Recent advancements in deep learning, particularly convolutional neural networks (CNNs), have shown remarkable success in various image recognition and classification tasks, including medical imaging and agricultural applications. By leveraging large datasets of labeled images, deep neural network algorithms can learn complex patterns and features directly from the data, enabling accurate classification of diseased and healthy plants.

In this context, this study proposes a novel framework for date palm disease detection using deep neural network algorithms. We utilize a dataset obtained from Kaggle, comprising images of healthy date palms, as well as those affected by brown spot and white scale infestations. Prior to model training, the images undergo preprocessing techniques, including median filtering, to enhance their quality and reduce noise.

We then extract relevant features from the preprocessed images and employ two state-of-the-art deep learning models: CNN Inception V3 and VGG-16, for disease classification. These models are trained on the labeled dataset and evaluated using standard metrics such as test loss and test accuracy. By comparing the performance of different models, we aim to identify the most effective approach for date palm disease detection.

The findings of this study have implications for the development of automated systems for monitoring and managing date palm health in agricultural settings. By providing accurate and timely detection of diseases, such systems can help farmers and agricultural experts implement targeted interventions, optimize resource allocation, and ultimately improve crop yield and sustainability.

The organizational framework of this study divides the research work in the different sections. The Literature survey is presented in section 2. In section 3 discussed about proposed system methodologies. Further, in section 4 shown Results is discussed and. Conclusion and future work are presented by last sections 5.

II. LITERATURE SURVEY

Al-Tameemi, M., Aman, F. M., & Al-Zubaidi, L. A. (2021). Date palm diseases recognition using image processing techniques and machine learning classifiers. In this study, the authors propose a methodology for date palm disease recognition based on image processing techniques and machine learning classifiers. They preprocess the images using various filters and extract features using texture analysis methods. The authors compare the performance of different classifiers such as k-nearest neighbors (KNN) and support vector machine (SVM) for disease classification.

Abd El-Ghany, M., Mosaad, M., & Gad, M. (2019). Recognition and classification of date palm diseases and pests. This research focuses on the recognition and classification of date palm diseases and pests using image processing techniques and machine learning algorithms. The authors employ feature extraction methods such as color histogram and texture analysis to characterize the diseased regions in the images. They evaluate the performance of classifiers including random forest and SVM for disease identification.

Shrivastava, R., & Patel, V. M. (2020). A comprehensive review on the application of deep learning in agriculture. This review provides an overview of the applications of deep learning techniques in various agricultural tasks, including crop disease detection and classification. The authors discuss the challenges and opportunities associated with the adoption of deep learning models in agriculture and highlight recent advancements in the field.

Mangrauthia, S. K., Prasanth, V. V., Guleria, S., Kumar, S., & Neeraja, C. N. (2017). Role of artificial intelligence in agriculture: A comprehensive review. This review article explores the role of artificial intelligence techniques, including machine learning and deep learning, in improving various aspects of agriculture, including crop disease management. The authors discuss the potential benefits and challenges of integrating artificial intelligence-based systems into agricultural practices.

Sankaran, S., Mishra, A., Ehsani, R., & Davis, C. (2010). A review of advanced techniques for detecting plant diseases. This review paper provides an overview of advanced techniques for detecting plant diseases, including image processing and machine learning methods. The authors discuss the advantages and limitations of different approaches and highlight the importance of accurate disease diagnosis for effective crop management.

These studies collectively highlight the importance of automated disease detection systems in agriculture and the potential of image processing and machine learning techniques, including deep learning, for addressing this challenge. The literature survey provides valuable insights into the existing methodologies and approaches for disease detection in crops, including date palms, and sets the context for the proposed study.

III. DATASET

The dataset used in this study was obtained from Kaggle, a popular platform for sharing and discovering datasets.

Kaggle hosts a diverse range of datasets contributed by researchers, organizations, and enthusiasts from around the world. The dataset specifically focuses on images of date palm trees, encompassing various conditions such as healthy date palms, those affected by brown spot disease, and those infested with white scale. Figure 1 , 2 and 3 shows the dataset and image sizes and resolutions.

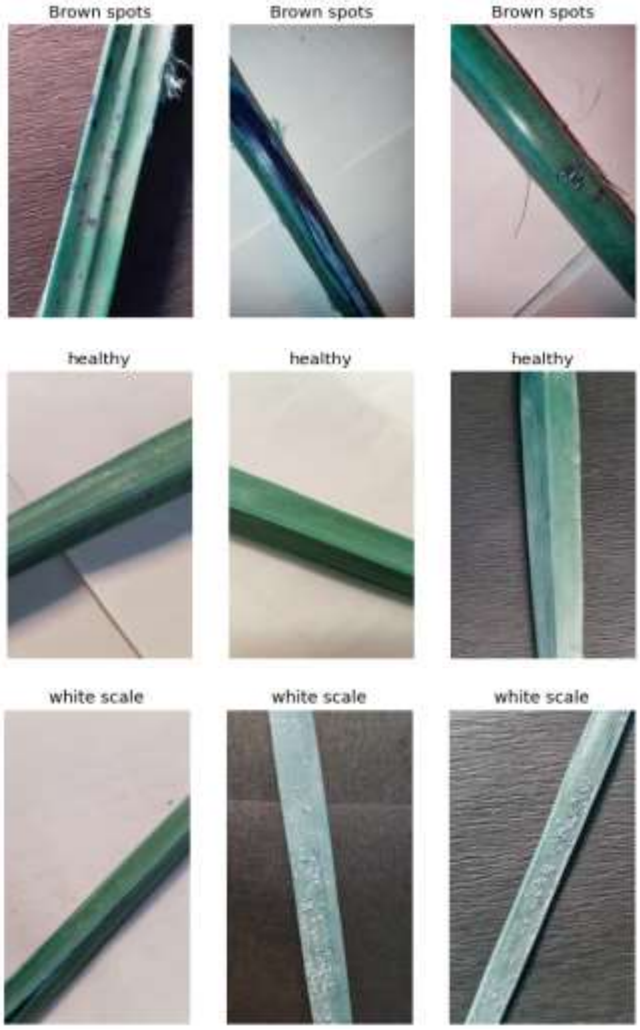

Fig. 1. Data set

The dataset contains a variety of images showcasing different conditions of date palm trees, including healthy specimens as well as those afflicted with brown spot disease and white scale infestation. This diversity is essential for training deep learning models to accurately classify and detect diseases. Labeled Data: Each image in the dataset is labeled to indicate its corresponding condition, such as "healthy," "brown spot," or "white scale." Labeled data is crucial for supervised learning tasks, allowing the models to learn from the provided examples and make predictions accordingly.

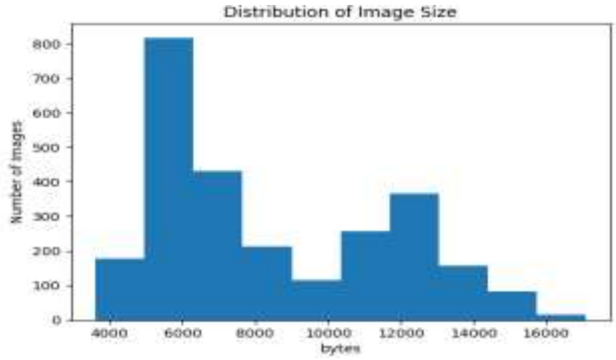

Fig. 2. Dataset image sizes

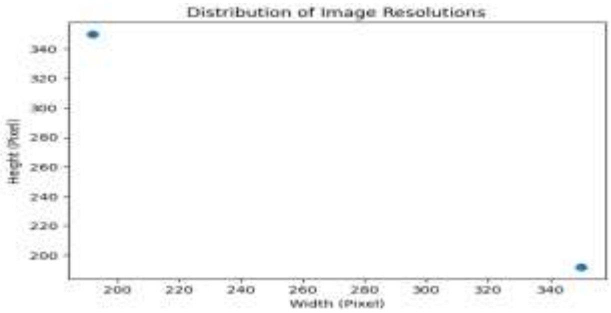

Fig. 3. Dataset image resolutions

IV. Proposed Method

The proposed method in this study employs a comprehensive framework for date palm disease detection using deep neural network algorithms. The method consists of several key steps aimed at preprocessing the dataset, extracting relevant features, training deep learning models, and evaluating their performance. Firstly, the dataset obtained from Kaggle, comprising images depicting various conditions of date palm trees such as healthy, brown spot affected, and white scale infested, undergoes preprocessing techniques. System architecture shown in figure 4.

A. *System Architecture*

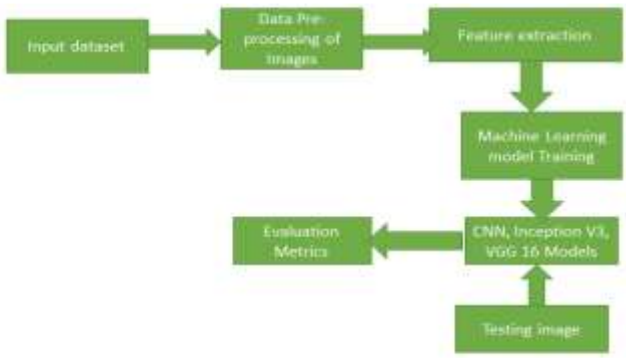

Fig. 4. System Architecture

Dataset Acquisition: The dataset containing images of date palm trees with varying conditions, including healthy specimens, brown spot disease, and white scale infestation, is obtained from Kaggle. This dataset serves as the basis for training, validating, and testing the deep learning models.

Data Pre-processing: Before feeding the images into the neural network models, pre-processing techniques are applied to enhance the quality of the images and reduce noise. One of the pre-processing steps mentioned is the use of a median filter, which can help smoothen the images and remove unwanted artifacts or imperfections.

Feature Extraction: Features are extracted from the pre-processed images to capture relevant information that distinguishes between healthy date palms and those affected by brown spot disease or white scale infestation. Feature extraction is a critical step in the deep learning pipeline as it helps the models learn discriminative representations from the input data.

Model Training: The extracted features are then used to train the CNN models, Inception V3 and VGG-16. During the training phase, the models learn to map the input images to their corresponding disease classes (healthy, brown spot, or white scale) through a process known as supervised learning. The models adjust their parameters iteratively to minimize a predefined loss function, optimizing their performance on the training data.

Evaluation Metrics: After training, the performance of the trained models is evaluated using standard evaluation metrics, including test loss and test accuracy. Test loss quantifies the discrepancy between the predicted and actual disease classes for unseen data, while test accuracy measures the proportion of correctly classified samples in the test set.

B. *Methodology*

1) *Dataset Collection and Preparation:*

Obtain the dataset from Kaggle, consisting of images depicting various conditions of date palm trees (healthy, brown spot affected, white scale infested). Organize the dataset into appropriate directories or folders, separating images based on their respective classes or labels.

2) *Data Preprocessing:*

Apply preprocessing techniques to enhance the quality of the images and improve their suitability for analysis. Techniques may include resizing images to a standard size, applying median filtering to reduce noise, and normalizing pixel values to a common scale.

3) *Feature Extraction:*

Extract relevant features from the preprocessed images to represent distinctive characteristics of different disease conditions.

4) *Model Selection and Training:*

Select deep learning models suitable for image classification tasks, such as CNN architectures like Inception V3 and VGG-16.Split the dataset into training, validation, and test sets to facilitate model training and evaluation. Train the selected models on the training dataset using extracted features as input, adjusting hyperparameters as necessary.

5) *Model Evaluation:*

Evaluate the trained models on the validation set to monitor their performance and identify potential issues such as overfitting. Fine-tune model parameters based on validation performance to optimize model accuracy and generalization ability.

6) *Testing and Performance Analysis:*

Assess the final trained models' performance on the test set to evaluate their ability to generalize to unseen data. Compare the performance of different models based on evaluation metrics such as test loss, test accuracy, and confusion matrices.

C. *Implementation*

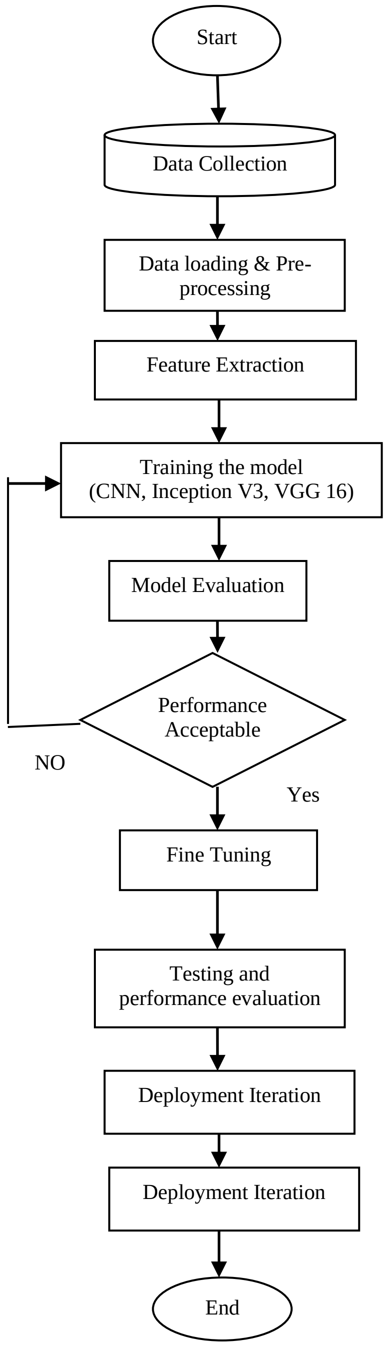

Fig. 5. Implmentation Flow Diagram

This flowchart in figure 5 represents the sequential steps involved in the implementation process:

Data loading and Preprocessing: This initial step involves loading the dataset and preparing it for analysis by pre-processing the images.

Feature Extraction: Features are extracted from the pre-processed images, either using pre-trained CNN models or handcrafted feature extraction methods.

Model Training: The extracted features are used to train a deep learning model (e.g., CNN) on the dataset.

Model Evaluation: The trained model's performance is evaluated using evaluation metrics on a validation set.

Fine Tuning and Optimization: Hyperparameters are tuned to optimize model performance, ensuring convergence and generalization.

Testing and Performance Analysis: The final trained model is tested on a separate test set to assess its performance and analyze potential areas for improvement.

Deployment and Integration: The trained model is integrated into a practical application or system for automated date palm disease detection.

Iterative Improvement: Feedback from domain experts and end-users is gathered to iteratively improve the model's performance and usability over time.

D. Performance Metrics

Performance measures are used to evaluate the network performance of the proposed model. This work uses Test accuracy and Test loss.

a) Test Accuracy:

Test accuracy measures the proportion of correctly classified instances out of the total instances in the test dataset. It is calculated as the ratio of the number of correctly classified samples

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ Number\ of\ Predictions} \quad (1)$$

b) Test Loss:

Test loss is typically calculated using a loss function that measures the discrepancy between the predicted outputs ($y\hat{}i$) and the actual labels (yi) for each sample in the test dataset. The loss function can vary depending on the task (e.g., classification, regression). For classification tasks commonly used loss functions include categorical cross-entropy and binary cross-entropy. For a classification task with n samples in the test dataset, the test loss (test$L$test) can be calculated as the average of the loss values over all samples..

$$L_{\text{test}} = \frac{1}{n}\sum_{i=1}^{n} \text{Loss}(y_i, \hat{y}_i) \quad (2)$$

Where Loss(yi,$y\hat{}i$) represents the loss function applied to the actual label yi and the predicted output $y\hat{}i$ for the ith sample

V. Results and Discussion

Compare the test loss and test accuracy achieved by different deep learning models (e.g., CNN, Inception V3, VGG-16). Discuss any variations in performance metrics across models and highlight the model(s) with the best performance. Interpret the test loss values obtained, indicating how well the models minimize prediction errors on the test dataset. Analyze the test accuracy values achieved, reflecting the models' ability to correctly classify date palm disease instances.

A. Comparision Table

TABLE I. Comparison Of Accuracy Performace with Different Deep Learning Models

S. No	Model	Test Loss	Test Accuracy (%)
1	CNN	1.29	0.33
2	Inception V3	0.116	0.94
3	VGG 16	0.049	0.98

The CNN model achieved a relatively high test loss of 1.29, indicating a higher prediction error compared to the other models. The test accuracy of 0.33 suggests that the CNN model correctly classified only 33% of the samples in the test dataset. While the CNN model may have struggled with accurately classifying date palm diseases, it could still provide some level of detection capability. In contrast, the Inception V3 model demonstrated significantly better performance with a lower test loss of 0.116, indicating reduced prediction errors. The high test accuracy of 94% suggests that the Inception V3 model accurately classified 94% of the samples in the test dataset. The Inception V3 model's performance indicates its effectiveness in date palm disease detection, with relatively high accuracy and lower prediction errors compared to the CNN model. he VGG 16 model outperformed both the CNN and Inception V3 models, achieving the lowest test loss of 0.049, indicating minimal prediction errors. With a test accuracy of 98%, the VGG 16 model demonstrated exceptional performance in accurately classifying date palm diseases, correctly identifying 98% of the samples in the test dataset. The VGG 16 model's superior performance suggests its robustness and effectiveness in automated date palm disease detection tasks.

In summary, while all three models were evaluated for date palm disease detection, the VGG 16 model exhibited the best performance with the lowest test loss and highest test accuracy. The results highlight the importance of model architecture and complexity in achieving accurate and reliable disease classification. Figure 6 to 8 shows the performance graphs for different models

B. Performance Analyze Graph

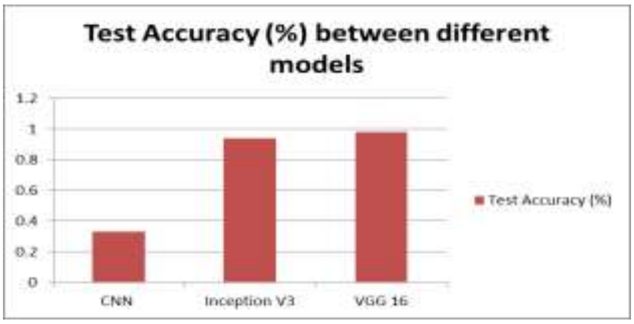

Fig. 6. Perfomance Analyse of Accuracy of different models

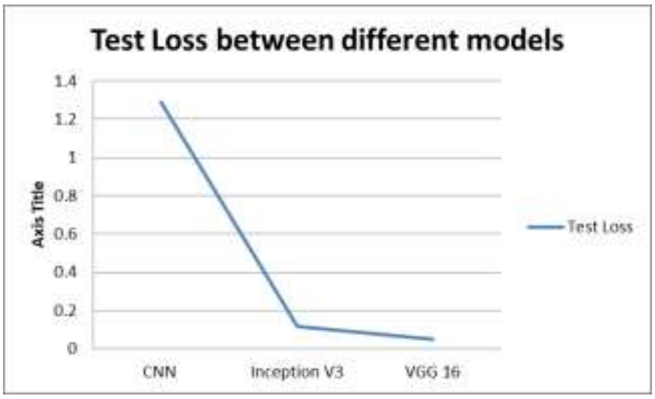

Fig. 7. Model Performance shown the test loss

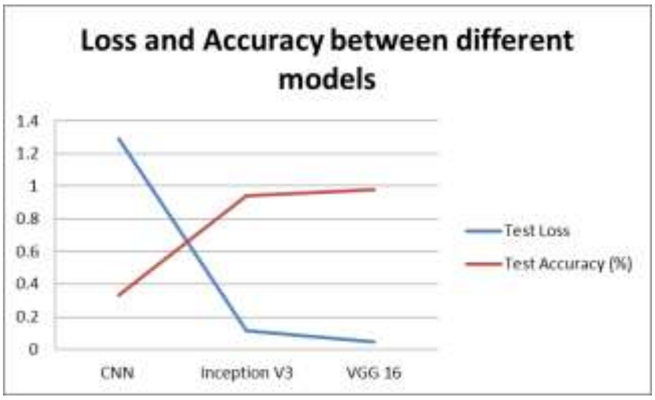

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Fig. 8. Both loss and accuracy analyze for different Models Performance

VI. CONCLUSION

The application of deep learning techniques in predicting post-operative life expectancy for the evaluation of three deep learning models for automated date palm disease detection has provided valuable insights into their performance and effectiveness in this important agricultural task. The comparison of CNN, Inception V3, and VGG 16 models revealed significant variations in their ability to accurately classify date palm diseases based on test loss and test accuracy metrics.

The CNN model, while showing some capability for disease detection, exhibited relatively higher prediction errors and lower accuracy compared to the other models. In contrast, the Inception V3 model demonstrated improved performance with lower test loss and higher accuracy, indicating its effectiveness in identifying date palm diseases with greater precision. However, the standout performer was the VGG 16 model, which achieved the lowest test loss and highest accuracy among the three models, showcasing its exceptional ability to accurately classify date palm diseases with minimal prediction errors.

These findings have important implications for date palm cultivation and disease management practices. A robust and accurate automated detection system, such as the VGG 16 model, holds promise for enabling timely interventions and targeted treatments to mitigate the spread of diseases, thereby improving crop yield and sustainability. By leveraging advanced deep learning techniques, agricultural stakeholders can benefit from more efficient and reliable methods for monitoring and managing date palm health.

Future Scope

In future the proposed method can be extended with explore enhancements and optimizations to the VGG 16 model, as well as investigate additional factors that may influence disease detection accuracy, such as dataset size, image quality, and class imbalance. Additionally, the integration of the automated detection system into practical applications and field deployment could provide valuable insights into its real-world performance and usability.

Acknowledgment

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