Deep Learning Tool-based Palm Tree Health Examination using Thermal Image Database

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Abstract. Plant health monitoring and pest handling are common practices in the agricultural domain, and the outcome achieved with this process helps to get complete information about the infection. This research considered the palm-tree image data for the examination, and it helps to detect the healthy/disease class of the date palm tree with improved results. This work considered the digital images collected with a thermal camera for examination and to achieve a better outcome, it considered the traditional DL models like VGG16, ResNet models, and DenseNet models for the examination. The different phases of this research include the following: data collection and resizing it to 224x224 pixels, feature extraction with a DL model, feature reduction, and generation of fused-features (FF) vector, detection using machine-learning classifiers, and confirming the result with 3-fold cross-validation. This work presented individual-features and fused-features based detection. This work considered the SoftMax and other related classifiers for examination. The outcome of this study confirms that the developed scheme can help to achieve a detection accuracy of >96% with the thermal image database. This work considered 700 images per class after augmentation, and the proposed tool works on this thermal image database and helps to achieve better results.

1 Introduction

Several countries still depend on farming to keep their economies stable and make sure they have enough food. This is especially true in places where people's jobs depend on how well crops grow and how healthy plantations are. In this setting, keeping an eye on plant health and controlling pests have become necessary methods for making sure that agricultural goods are made in a way that is good for the environment. Farmers can use fewer pesticides and lose less yield when they can quickly and accurately identify plant diseases. This is good for the environment. Automated, data-driven systems that can give reliable and timely information about the health of crops are slowly replacing traditional manual inspection methods. This is a direct result of how quickly precision agriculture is growing. In dry and semi-arid areas, date palm trees are one of the most important perennial crops. They help the economies of the areas around them, create jobs, and grow a lot of food. On the other hand, date palms are very susceptible to many diseases and pest infestations, some of which may not be found until later stages. In many cases, visible symptoms such as discoloration, wilting, or structural damage only become apparent after the infection has already progressed to an advanced stage. This makes it hard and time-consuming to check things out in person. Because of this, there is a big need for advanced monitoring systems that can spot small changes in the physiology of palm trees before the obvious symptoms get worse. Recent advances in computer vision, machine-learning (ML), and deep-learning (DL) have opened up new possibilities for automated diagnosis of plant diseases. Standard RGB photos have been used a lot to classify plant diseases, but these photos are often affected by changes in light, shadows, and noise from the background. These limitations could make disease detection systems in agricultural settings much less reliable and useful in the real world [1,2].

Thermal imaging has been getting a lot of attention in agricultural research lately to help with these problems. Thermal cameras are used to record changes in temperature on the surfaces of plants. These temperature changes are closely linked to physiological processes like transpiration, water stress, and metabolic activity. By simply analysing the images captured with the thermal camera, it is possible to predict the plant's health accurately. During this process, the thermal images of the healthy and the disease cases are collected, resized and labelled for training and verifying the performance of the developed system and this model, which was trained, is then considered to analyse the condition of the

plant. Recently, the DL-models have played a big role in the revolution in image analysis by making it possible to automatically extract features from raw data. This change happened at the same time as changes in sensing technology. The considered DL-models help in achieving better outcomes during image examination compared to the traditional ML techniques, and hence, DL-based digital data handling is commonly adopted by the researchers [3,4].

This research aims to plan and implement a DL-model-based tool for analysing the healthy and infected trees based on the thermal images. The thermal images, which are labelled and kept in a data repository is then considered for the examination and the outcome is then analysed to verify the performance of the developed scheme. In this work, the traditional DL-model-based approaches are adopted to evaluate the performance on the plant health monitoring process. Different phases considered in the developed system include the following: image collection and modifying its size based on the DL-algorithm's requirement, extraction of the deep-features using the DL-model, classification of the considered images using the SoftMax classifier, and verifying the merit of the developed system using 3-fold cross-validation [5,6].

This work considered the traditional DL-models to verify their performance on the considered image data, and it achieved a better detection result on the images adopted for the examination. The main merit of this research is that it considered only the pre-trained models that work based on the transfer learning concept, and it achieved better detection results, and in some models, the detection result is around >96%, which confirms the merit of the implemented scheme.

The main contribution of this research includes;

(i) Development of the DL-model for analysing the healthy and infected trees based on the thermal image database,

(ii) Analysis of the performance of the considered DL-model using the SoftMax classifier and confirming the merit of the system.

2 Literature review

Due to its significance, several plant health monitoring systems based on image data is commonly adopted in recent years. Most of these works considered the conventional image data for analyzing the performance of the developed system. Some recent works considered the thermal images of the plant to identify its health condition. This approach worked well on several image databases, and some works considered for the demonstration are depicted in Table 1 along with the procedure considered and its outcome.

Table 1. Comparative Analysis of Existing Methods

Reference	Methodology	Achieved results
Nadeem et al., 2025 [7]	Collected thermal images of date palms in field groves, annotated for Red Palm Weevil (RPW) infestation. Images were standardized and preprocessed (resizing, normalization). Baseline classifiers and DL feature extractors were run to provide benchmarks and to support subsequent supervised experiments and data-augmentation strategies.	Curated dataset + baseline classification benchmarks enabling follow-on DL experiments (dataset published; classification baselines reported).
Delalieux et al., 2023 [8]	Used multi-date thermal UAV imagery to build temporal signatures of palm canopy temperature. Extracted per-tree thermal time-series, computed temporal anomalies and spectral indices, and applied supervised classifiers to detect RPW infestations before visible symptoms. Emphasis on temporal deviation from normal phenology.	Demonstrated thermal UAV + temporal analysis can detect RPW earlier than visual inspection; good discrimination and timely alerts in test orchards.
Alsadik et al., 2024 [9]	Reviewed UAV platforms with thermal cameras, acquisition protocols, georeferencing, and radiometric calibration for palm health. Compared thermal feature extraction workflows (histograms, texture, canopy temperature) and ML pipelines; recommended standard flight heights and repeated surveys for temporal monitoring and early pest detection.	Synthesized best practices: UAV-thermal is effective for palm health monitoring; recommended protocols improve detection reliability and operational adoption.
Mir et al., 2025 [10]	Proposed a hybrid DL ensemble combining thermal and hyperspectral features. Thermal images supplied temperature-based cues; hyperspectral images provided biochemical signatures. Features fused at the representation level, dimensionality reduction applied, and an ensemble classifier used to detect disease/pest stress with improved sensitivity to early infection markers.	Fusion of thermal + hyperspectral with ensemble DL improved early detection sensitivity compared to either modality alone.
Gibril et al., 2024 [11]	Employed transformer-based architectures on multisensory aerial imagery, including thermal layers to identify, count, and assess palm trees at scale. Data preprocessing included radiometric correction and patching; the transformer model learned spatial-temporal dependencies and provided per-tree health scores for prioritization.	Achieved robust large-scale monitoring with accurate tree detection and coarse health scoring; thermal bands boosted water-stress/pest sensitivity.
Savaş et al., 2024 [12]	Applied an ensemble of CNN backbones (e.g., ResNet, DenseNet) to palm imagery and fused features; used feature selection to reduce redundancy. Thermal inputs were used where available; classifiers (SVM, SoftMax variants) were trained on fused vectors and evaluated via cross-validation for robust detection of disease classes.	Ensemble + feature fusion improved classification robustness and boosted accuracy compared to single models; thermal inputs contributed to higher recall for stressed trees.
Alaa et al., 2020 [13]	Captured visible and thermal images (mobile/thermal camera). Applied preprocessing, image enhancement, segmentation, then trained a VGG-style CNN for leaf spot/blight and used SVM for RPW detection on thermal images. Dataset augmentation and a smartphone app prototype were part of the pipeline.	Reported high accuracies: CNN ~97.9% for leaf diseases; SVM ~92.8% for RPW detection on their thermal dataset. Demonstrated mobile/thermal feasibility.
Vidal et al., 2019 [14]	Reviewed infrared thermography (IRT) applied to tree and wood health: acquisition, calibration, influence of environmental	IRT is non-invasive and effective for detecting structural problems, water stress, and

	factors, and data interpretation. Discussed methods to segment canopy, correct for solar loading, and link thermal anomalies to internal decay, water stress, or pest activity.	anomalies, but requires careful calibration and environmental control for reliable field use.
Rasool et al., 2019 [15]	Evaluated thermal cameras alongside other non-invasive devices for tree health assessment. Compared measurement protocols, sensor performance, and detection metrics. Emphasized preprocessing steps (noise removal, normalization) and the utility of thermal imaging to detect moisture and physiological stress related to pests/disease.	Found thermal cameras useful for detecting water stress and internal issues; performance depends strongly on acquisition protocol and environmental conditions.
Golomb et al., 2015 [16]	Early work using aerial thermal imaging to estimate palm water status and infer pest/damage. Employed radiometric aerial surveys, canopy segmentation, and temperature thresholding to locate anomalous palms. Proposed methods for discriminating soil vs canopy heat and detecting stressed trees for targeted inspection.	Demonstrated that aerial thermal surveys can flag stressed palms and support targeted field inspections; early proof-of-concept for thermal RPW detection.

The values presented in the table 1 demonstrate that prior research on thermal image–based analysis is effective and yields improved detection performance. Hence, this work also considered a similar procedure with the DL technique and achieved a better detection outcome with several DL models along with SoftMax classification.

3 Methodology

The performance of the digital data evaluation task depends mainly on the procedure that was developed and implemented to analyse the image dataset. The proposed technique helps in implementing the deep-learning scheme for the data analysis, and the outcome is then verified to confirm the significance of the system.

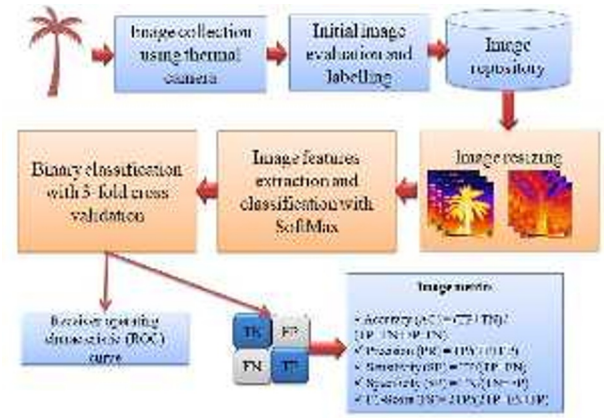


Fig. 1. Proposed architecture to detect the tree health using thermal images

The initial part demonstrates the collection of the plant data using the considered drone-camera-based approach, and these images are then normalised and enhanced to detect the abnormalities manually, and then labelled appropriately based on the examination. The labelled images are then stored in the data repository for future use. This work considered the images found in the data repository, and then the required images were collected and considered for examination after the necessary image resizing task. The images are then considered for the feature extraction, and then the feature-based analysis for the identification of healthy/diseased plants. This work performed the plant image classification using the individual-features and Fused-Features (FF) with the SoftMax-based classification, and the achieved results are confirmed based on the accuracy and the ROC-value attained with this research. The experimental outcome of this study confirms that the proposed approach helps in achieving better detection results on the considered image database.

3.1 Thermal image data

To verify the performance of the developed DL-scheme and to confirm its merit with the real images collected using the considered imaging scheme, it is necessary to use standard images that work well on the academic task and the real-time examination process. Hence, several guidelines are provided in the literature to use appropriate image data, and this work considered the thermal image database found in [17] for the study.

This research considered the images after implementing the necessary data augmentation and resizing, and from every case, around 1200 images were considered for the analysis. The total number of images used in this study, along with the adopted data split and related details, are summarized in Table 2. Representative sample images from the dataset for both healthy and infected classes are illustrated in Figure 2. These images are then considered to verify the performance of the developed DL-scheme.

Table 2. Thermal image data from each tree class

Image class	Thermal images for the evaluation			
	Total	Train	Validate	Test
Healthy	1200	960	120	120
Infected	1200	960	120	120

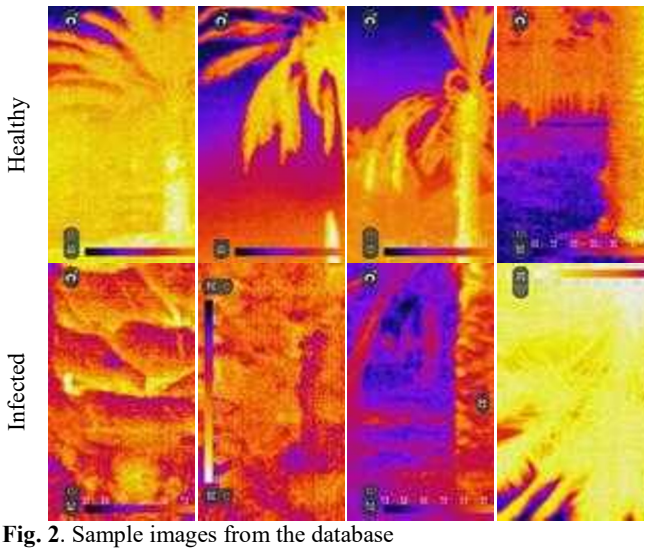


Fig. 2. Sample images from the database

3.2 Deep learning scheme

Selection of a suitable computer-algorithm is necessary to verify the merit of the developed system, and this work considered the pre-trained DL-models commonly employed in recent research works. To verify the model's merit, it is necessary to identify a suitable scheme and then verify its merit based on the classification result.

To achieve this, this research considered the common DL-schemes, like the VGG16, ResNet-models (RN50, RN101, RN152), and DenseNet-models (DN121, DN169, DN201), and these models are verified using binary classification. To achieve a better outcome from this scheme, the following values are assigned for these models: monitoring values= accuracy and loss, activation= ReLU, optimizer= Adam, pooling= max, learning rate= 1e-3, batch size= 8, and classifier= SoftMax [18,19].

3.3Features fusion and classification

In most of the data examination tasks with the DL-scheme, the individual feature-based examination may not provide a better outcome, and hence, the modified features, the fused-features, and ensemble-features are commonly considered to achieve a better outcome. This work considered the FF-based examination commonly discussed in the literature [20].

The development of the FF-involves in identification of the best DL-models based on the achieved accuracy during the SoftMax classification task, and then these model features are reduced to 50% after ranking the features, and these two model features are then serially combined to get a single FF, which is then considered to classify the considered image data. This FF is efficient in attaining a better detection result on the image data, and its outcome is better compared to the individual features-based detection, which is common in the traditional DL-scheme implementation.

3.4Performance verification

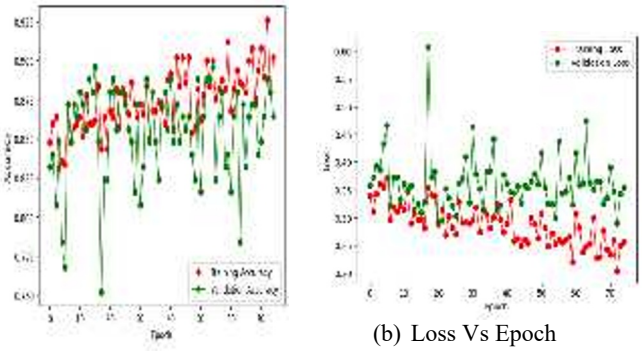
The analysis done with the Python program showed that the built DL-scheme was useful for the picture database that was taken in. This was done to get more information. The computer that does this has an Intel Core i5 processor, 20GB of RAM, and 4GB of VRAM. During the verification process, the image performance data acquired through CM and ROC-curve are employed. The study's results show that the strategy used works to improve the results of cancer detection by using histopathology databases. The conclusions of the study provided this evidence.

4. Result and Discussion

This section displays and examines the experimental inquiry that was carried out in order to make use of the DL tool that was recommended. The first step in this investigation is the implementation of individual feature-based detection, and then the next step is the implementation of DL-based classification.

First, the VGG16-model is taken into consideration before the SoftMax algorithm is used to classify the tree image database. The outcomes of the training and validation, which were carried out over the course of 75 epochs, are presented in Figure 3. The accuracy and loss that were accomplished through the utilization of this strategy are depicted in Figures 3(a) and (b). Figure 4 illustrates the results obtained by applying a number of different VGG16-model layers to a sample image in order to demonstrate the result of converting pixels into features. The layer1 to layer4 for the image are displayed in Figs. 4(a) to 4(d). It can be seen in Figure 5 presents the ROC-curve attained for VGG16 during the testing process, and this value is 0.9355, which confirms the merit of the VGG16 on this database. A process that is quite similar to the one that was described earlier is utilized in order to validate the performance of the DL-model with particular characteristics. The outcomes that are obtained from this procedure are presented in Table 3. A successful completion of the features-based data classification using SoftMax has been accomplished with individual-features and FF.

The results demonstrated in Table 3 confirm that the developed system provides an accuracy, which varies from 96.5% to 98.75% on the given image data when the SoftMax classifier is considered, and this result confirms that the developed system works well on this database and helps to identify both the healthy and the infected trees accurately during the implemented classification task.



(a) Accuracy Vs Epoch (b) Loss Vs Epoch

Fig. 3. Initial training outcome with VGG16

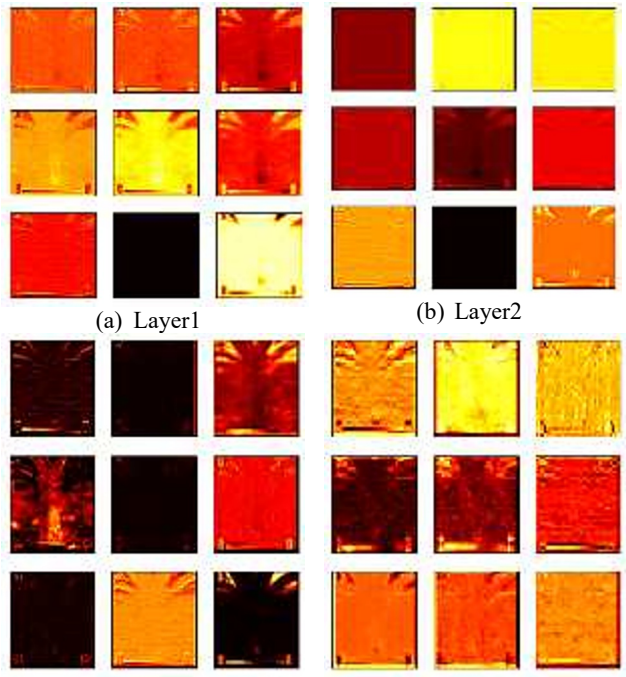


Fig. 4. Different layer results with VGG16

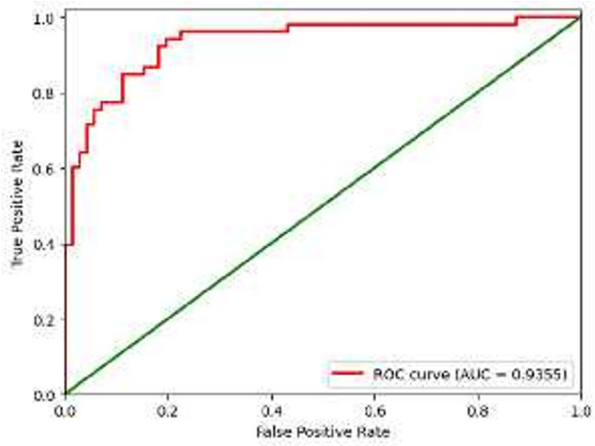


Fig. 5. Final result to demonstrate the ROC-value

Table 3. Performance evaluation of DL-scheme with individual features and FF with SoftMax

Model	TP	FN	TN	FP	AC	PR	SE	SP	FS
VGG16	116	4	118	2	97.50	98.3051	96.6667	98.3333	97.4790
RN50	114	6	117	3	96.25	97.4359	95	97.50	96.2025
RN101	117	3	115	5	96.6667	95.9016	97.50	95.8333	96.6942
RN152	118	2	115	5	97.0833	95.9349	98.3333	95.8333	97.1193
DN201	114	6	116	4	95.8333	96.6102	95	96.6667	95.7983
DN169	113	7	117	3	95.8333	97.4138	94.1667	97.50	95.7627
DN201	119	1	113	7	96.6667	94.4444	99.1667	94.1667	96.7480
FF	118	2	119	1	98.7500	99.1597	98.3333	99.1667	98.7448

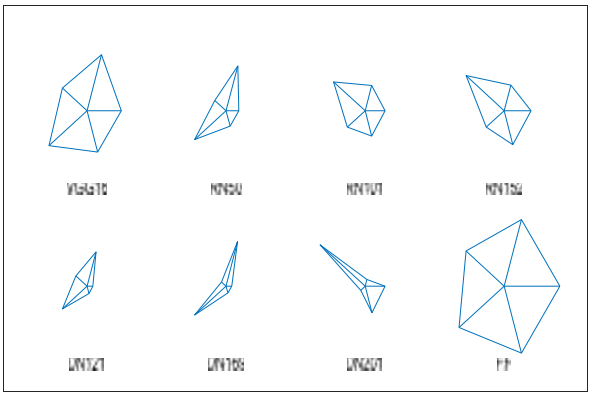


Figure 6. Overall outcome of this system with Glyph-plot

The outcome shown in Table 3 verifies that the developed system works well on this image database. To demonstrate the overall performance, a Glyph-plot is also constructed for the Table 3 values, as in Figure 6. These figures also confirm that the FF-based detection helps to attain a better result on this database. This confirms that the developed system is efficient in detecting the tree condition, and in the future, it can be used to evaluate the thermal images, which are obtained with a suitable imaging system.

5 Conclusion

This research aims to propose a straightforward and efficient tree health identification tool based on the DL-model. This research proposes the creation of such a tool for analysing the healthy and infected trees based on thermal images. Through the utilization of this technique, the classification of trees will be improved in terms of its accuracy. For constructing the developed scheme, pre-trained DL-models were taken into consideration. Additionally, the tool that was produced was put into action and tested with the assistance of Python-software. This work made use of the SoftMax-classifier in order to take into consideration the classification procedure, which consisted of evaluations based on the achieved detection results with conventional and FF. The overall outcome of this research confirms that the FF-based approach provided 98.75% on this image examination task.

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