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AI-ENABLED FRAMEWORK FOR INTELLIGENT DATE FARMING IN SMART AGRICULTURE

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Abstract

Agriculture is the backbone of the economies of many countries globally, contributing significantly to food security and poverty eradication in the nation. It not only provides sustenance but also feeds various industries raw materials like textiles, pharmaceuticals, and fuel production. Date cultivation is significant in Saudi Arabia's agriculture. It is one of the major pillars of the nation's agriculture and makes a significant contribution to the nation's economy, thus becoming one of the global leading producers of dates. Diseases that have the capability to destroy date palm groves and limit harvests considerably are among the most crucial challenges. Diseases can be major contributors to economic losses through harming both local consumption and global exports. Disease diagnosis via conventional methods is complicated and unreliable. The unstable climate of Saudi Arabia also contributes to the challenge of the date farmers. In order to overcome these challenges, the suggested AI-based system that utilizes cutting-edge technologies like computer vision and deep learning provides an apparent solution. The technique can help with early treatment and intervention by rapidly and accurately identifying disease in date crops via computer vision algorithms. In addition, its capability to process huge amounts of environmental data collected through sensors and unmanned aerial vehicle (UAVs) allows for precise predictions and knowledge-based crop management decisions. 6G technology integration can ensure ultra-fast and secure connectivity, allowing smooth communication between the system and internet of things (IoT) sensors. This will enable the system to gather real-time information on different environmental and agricultural parameters, including temperature, humidity, and soil water levels, which may affect date crop health. Thus, by bringing together and putting in place cutting-edge technologies, we can reinvent the agriculture sector in an entirely new and revolutionary manner.

Keywords—Smart Agriculture; AI; Dates farming, Computer Vision.

I. INTRODUCTION

This ambitious project is a journey of transformation in farming, with dates crop cultivation as the point of departure. The venture is based on a multi-dimensional technological strategy that eclectically integrates Artificial Intelligence (AI), Computer Vision, and internet of things (IoT) [1]. Underlying this study work is the desire to attain several critical objectives. It strives

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to lead the way in early disease diagnosis in date crops using AI and Computer Vision, empowering farmers with unprecedented information and the ability to effectively prevent crop diseases [2]. Combining IoT and 6G tech brings data-driven, real-time crop management, facilitating precision agriculture and optimization of resources. Whereas this project imagines a future of technologically advanced agriculture, it recognizes some challenges in the form of upfront costs of implementation, security issues, and the need to develop ethical and legal frameworks [3]. In spite of all these challenges, the project is an example of the boundless possibilities of technology-based agriculture that defies dates to fuel a revolution that will go beyond changing farming methods in the world. It is a shining example of innovation, sustainability, and prosperity for the farming industry, marking the beginning of an era of agricultural excellence and advancement [4]. Figure.1 illustrates the assumed scenario, comprising IoT sensors, and smart devices on the dates' farm.

Figure 1 Considered scenario for date farming

The main contributions of the paper are as follows:

1. Developing AI-enabled framework for the date farming to automate agriculture landscape.
2. Implementation of the deep learning models on the dates dataset to determine the health of the date plant.
3. Performance evaluation of the proposed models.

Rest of the paper is organized as follows: Section 2 describe literature review, while methodology is presented in section 3. Section 4 presents results, followed by discussion and conclusion.

II. Literature Review

Saudi Arabia holds the second position in global date palm production, dedicating 157,000 hectares of land to this crop and yielding 1.1 million tons of dates annually [5]. Across various regions of Saudi Arabia, around 450 different date palm cultivars have been cultivated [6]. Black scorch disease has emerged as a destructive threat to date palm cultivation in the Arabian Peninsula. Morphological examination has also established the existence of Thielaviopsis punctulata as a suspect causing this disease in date palm plant samples. In addition, we also carried out experiments with seven fungicides found in the market to gauge their performance in managing black scorch disease. Interestingly, in vitro treatments using three of these fungicides, Aliette, Score, and Tachigazole, achieved remarkable inhibition of the fungal growth area by 86–100%. Black scorch disease is a serious menace to the date palm industry and may result in losses of up to 50% in newly planted off-shoots [7]. Reducing the use of chemical fungicides through adopting integrated disease management (IDM) practices can go a long way in controlling the disease [8],[9]. Saudi Arabia alone produces about 9 million tons of dates and contributes about 17% of the world's total production [10].

Under the local climate of Saudi Arabia, date palm trees are prone to a number of destructive diseases that result in the loss of trees and their yield. A number of soil-borne fungi cause root rot, wilt, and decline diseases in date palms [11]. Notwithstanding the challenges, Saudi Arabia has given top priority to the development of its agricultural sector because of its significance for food security and job opportunities. The nation is independent in date, meat, milk, and poultry production, even exporting excess products to overseas countries [12]. With a total of 25 million palm trees that yield approximately 1 million tons of dates per year, Saudi Arabia supplies 15% of the world's production of dates [13],[14]. The Al-Hassa oases are the biggest palm-producing region in Saudi Arabia and are home to about 3 million palms, among which the predominant cultivar is Khalas date [14],[15]. Three water sources of irrigation are utilized within Al-Hassa, including desalinated water, recycled wastewater, and groundwater from free-flowing springs, each alone or in combination. But because of rising demand for agricultural development and urbanization, most free-flowing springs no longer flow naturally because of over-exploitation and depletion in groundwater [16],[17],[18].

The most widely cultivated cultivars in Al-Hassa are Khalas, Ruziz, and Shishi, with Khalas making up 73% of date palms in Al-Hassa [19]. Khalas is globally famous as one of the superior date palm cultivars. The productivity of the region, however, remains relatively low owing to such reasons as the shortage of available offshoots for establishing new orchards and the high cost of quality cultivar offshoots. Other challenges include poor farm management, inadequate integrated pest management (IPM) control, subpar harvesting and processing, water scarcity, and a shortage of qualified and trained labor [13],[19].

Furthermore, other components of the date palm also have important positions in the economy of agriculture. Date palm stems are employed in the manufacture of boats, while the fibers and leaves are utilized for roofing rural homes, paper making, wood industries, and crafts such as fans, baskets, and straw hats [20]. In order to resist the environmental pressures of climate change [21], the palm sector in Al-Hassa needs to shift towards sustainable agriculture systems by optimal water and fertilizer usage, better agricultural practices, better fertilization practices, better harvesting techniques, growing suitable cultivars, and greater IPM strategies. The monoculture system with Khalas has a threat of increased vulnerability to pests and diseases, owing to the long-life cycle of date palms [14],[22],[23]. In addition, the use of digital technologies, including remote sensing and big data analysis, can improve date production by ensuring higher yields, minimizing losses, and averting risks while conserving resources like water, energy, fertilizers, and pesticides [24]. The introduction of precision agriculture

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technology could potentially raise crop production much higher by 2050 [25],[26]. Precision application of fertilizer can increase the yield by 18%, precision planting by 13%, precision spraying by 4%, and precision irrigation by 10%, supporting more environmentally friendly practices [27]. Software such as CLIMEX, applied for eco-climatic modeling, can give early warning scenarios for environmental managers to act promptly on shifts in the Saudi Arabian distribution of date palms. Nevertheless, note that the production of date palms is labor-intensive, with a need for skilled labor, hence relatively high operation costs. Therefore, the lack of water resources in light of climate change and limited availability of skilled labor are overwhelming challenges and cost implications in increasing date palm production in the future.

III. METHODOLOGY

The next section discusses data set and model implementation for this research.

The dataset was obtained from the [28], which have three classes for the dates, healthy, brown-spot and white-scale. The samples are indicated in the subsequent figures.

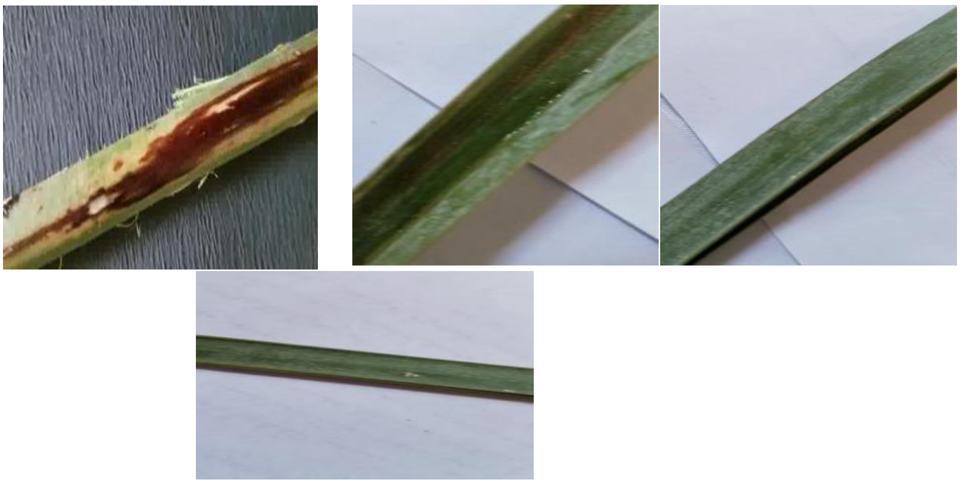

Figure 2 Samples from the dataset.

The work flexibility goes beyond dates to other agricultural crops and fields. It also focuses on the imperative establishment of ethical and legal structures for farm technology, reflecting a deep commitment to responsible data application. In short, this project is not only pioneering; it's visionary in its potential to reshape modern agriculture globally. This research effort is principally rooted in a systematic and rigorous methodology aimed at guaranteeing both its intellectual solidity and practical relevance. The first step is a thoroughgoing needs assessment, carried out by a mixed-methods combination of questionnaires and in-the-field interviews with farmers and agricultural actors throughout the Kingdom of Saudi Arabia. This analytical stage goes beyond supposition to accurately determine and record the greatest needs, with particular emphasis on the ruinous effect of plant diseases, the economic necessity of maximizing yields, and increasing demand for credible ethical and sustainable approaches in the date palm supply chain. Acting upon these needs so ascertained, the research advances to a careful technology selection phase. In this, an extensive literature review is made of digital agriculture to find and rationalize the most appropriate and transformation technologies. The study hypothesizes that

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there needs to be a synergistic technology stack, and therefore it strategically combines Computer Vision (CV) and Artificial Intelligence (AI) for rich analytic and visual recognition, a rich mesh of Internet of Things (IoT) sensors for real-time environmental monitoring, and the theoretical basis of future 6G connectivity in order to conceptualize a seamless, high-fidelity data pipeline capable of accommodating the enormity of data required by the envisioned system. The essence of the analysis work is in the training and building of complex AI models. In the case of disease detection, the research work utilizes state-of-the-art deep architectures, such as Convolutional Neural Networks (CNNs) such as AlexNet and GoogLeNet, and newer transformer-based models such as Vision Transformer (ViT) and Swin Transformer. These are trained on a large, curated, and annotated set of date palm images to learn and identify sophisticated visual patterns of disease-related discoloration, wilting, and morphological deformation. At the same time, the other AI models correlate the merged data streams from IoT sensors, UAVs, and past yield records to execute predictive analytics for crop yield and productivity in general, capturing complex relations among environmental conditions and ultimate output. Finally, the research paper incorporates a critical testing and validation step to ensure scientific integrity. The disease detection and yield prediction model performance is strictly tested on a held-out test dataset. This includes quantitative measures of accuracy, precision, and recall, and most importantly a validation step where the model outputs are matched against expert-agronomist validated "ground truth" data gathered from the same fields. This iterative process of testing and refinement is essential to ensure the system's predictions are not only computationally sound but also agriculturally accurate and dependable for end-users**.** The overall proposed method is shown in the figure 3.

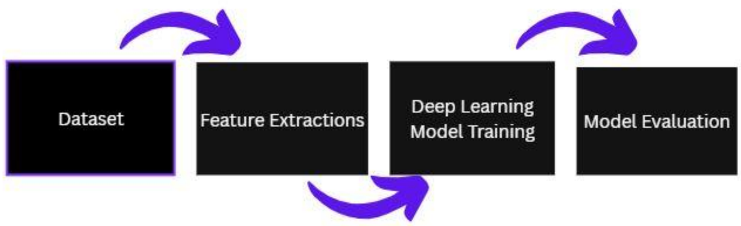

Figure. 3 Proposed Methodology of the work

IV. RESULTS AND ANALYSIS

In this research study we have employed state-of-the-art deep learning models which include a custom CNN, GoogleNet, AlexNet, and Swin Transformer, and ViTs. The evaluation of these models was done on a publicly available dataset, the Date Palm Dataset (Hadjer Hamaidi, Kaggle) [28]. The dataset includes images of date palm leaves with three distinct classes: healthy leaves, brown spot disease, and white scale infection. On first glance, the unequal class distribution suggests that there is a class imbalance which if not handled properly could lead to biased accuracy.

1. **Custom Convolutional Neural Network (CNN) with custom layers:**
The custom CNN model [29] achieves an accuracy of 98.86 % highlighting that a carefully designed architecture which is tailored towards the visual characteristics of the date palm leaves can compete with the large pre-trained models. The smaller parameter counts enables the

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model gets trained faster and also is less prone to over-fitting, especially when combined with data augmentation.

2-LayerCNN(CNN-3L)

The 3-layer CNN indicates a clear trend of gradual convergence between the training and validation sets. The loss curves as shown in the figure 4 indicate a steady learning with minimal divergence between training and validation losses and the accuracy curves show a strong improvement up to ~90–95% after few epochs, which reflects a effective feature extraction even with limited depth.
However, there is a minor fluctuations in validation accuracy, which can be interpreted as the sensitivity to the data variability, implying that sometimes the model over-fits to the training distribution. The confusion matrix indicates that the model is performing well as it classifies most of the samples properly with the predictions of healthy leaf (180/181) and brown spot (71/72) being almost perfect with a few white scale samples being miss classified as healthy. This means that, the 3-layer network is able to capture most of the features but sometimes it lacks sensitivity to precise inter-class differences, especially between healthy and mildly diseased leaves.

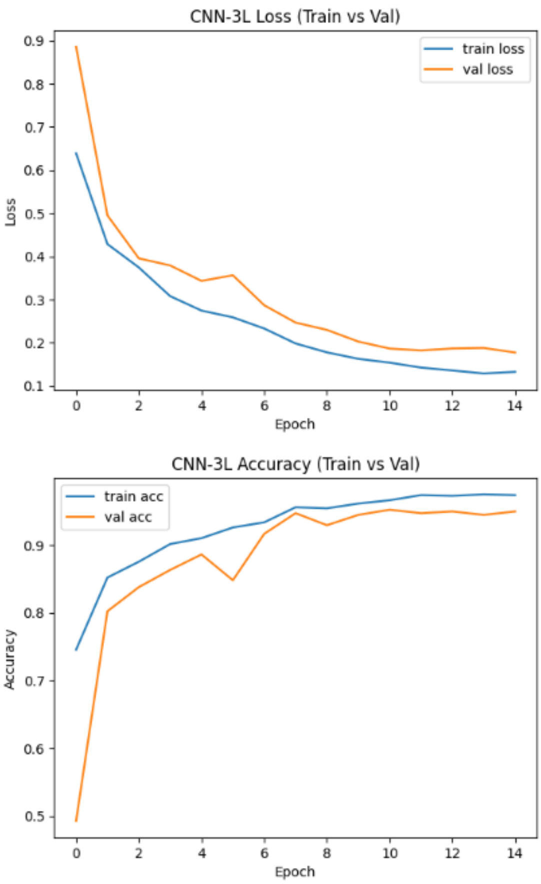

Figure.4 Training – validation loss and accuracy curves for CNN-3L and CNN-4L models

3- **Layer CNN (CNN-4L)**

The 4-layer CNN shows gradual convergence and a more prominent reduction in the training

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and validation losses, indicating better generalization. The validation accuracy follows the training curve, approaching 98–99%, which means that the architecture is effective in over-fitting mitigation while capturing more complex visual cures. In the confusion matrix as shown in the figure 5, the 4-layer CNN shows almost a perfect classification of all the three categories with only a few miss-classifications (e.g., 1–2 samples per class). This indicates that the model's increased discriminator ability and confirms that the added layer depth contributes to more robust feature hierarchies, improving precision and recall across classes.

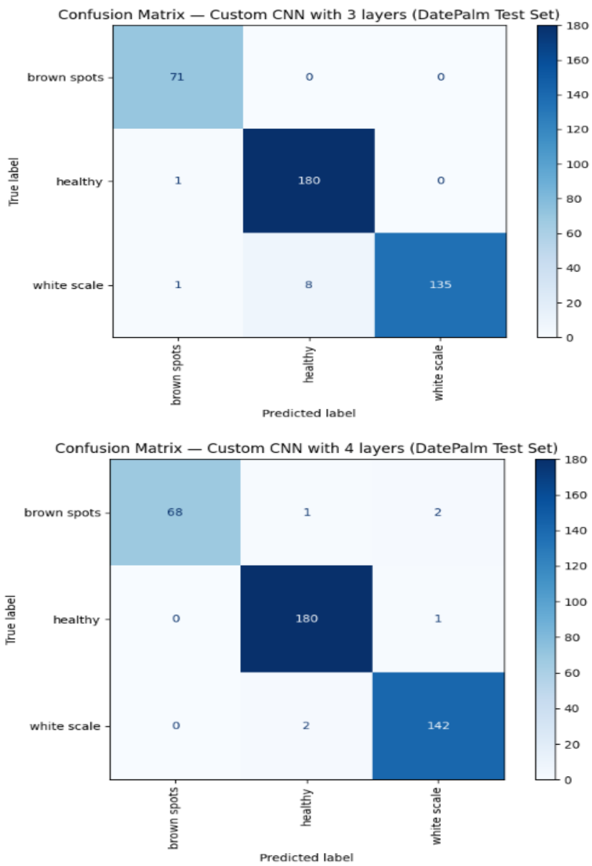

Figure.5 Confusion matrix of Custom CNN with 3 layers (CNN-3L) and 4 layers (CNN-4L)

2. CNN with attention mechanism

The CNN with an attention mechanism demonstrates better convergence behavior than the original CNN models. Training and validation loss decreases continuously with minor variation, indicating high generalization capabilities. Accuracy also increases quite fast within the initial few epochs and stabilizes near 96% to 97% for both training and validation as shown in the figure 6, confirming that the attention mechanism enables the network to selectively focus on the most relevant features of the leaf images. This not only accelerates learning but also reduces over-fitting, making the attention-based CNN a robust candidate for plant stress classification.

The confusion matrix as shown in the figure 7 further confirms this performance: the majority of samples are correctly classified, with less miss-classifications, only a few healthy and white

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scale images are confused as they have a similar appearance. Precisely, the model accurately identified 177/181 healthy, 68/71 brown spot, and 136/144 white scale samples. These results show that the attention-based CNN is not only faster to learn but also more interpret-able and robust features, which makes it a strong candidate to be applied in more practical plant disease detection and stress classification tasks.

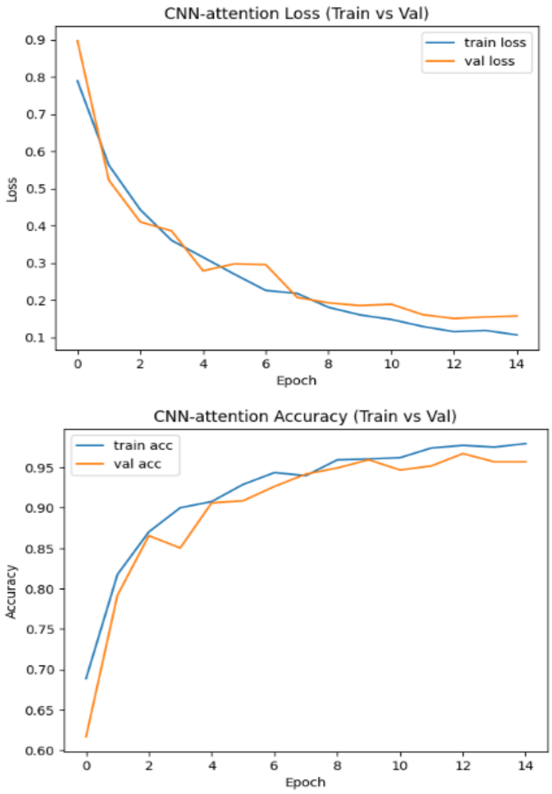

Figure.6 Training – validation loss and accuracy curves for CNN with attension mechanism

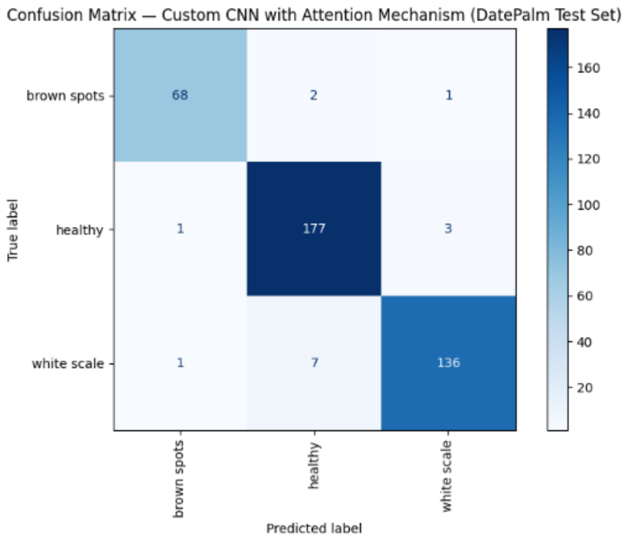

Figure.7 Confusion matrix of CNN with Attention Mechanism

3. CNN with Skip Mechansim

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The CNN model integrated with a skip connection mechanism exhibits strong convergence and stable generalization behavior. Both the training and validation loss curves as observed in the curves decrease steadily throughout the epochs, reaching low and almost parallel values at the end of training process. This trend implies an effective learning and minimal over-fitting. The training loss decreases consistently, and the validation loss also drops rapidly at the initial epochs, indicating that the model efficiently describe the most crucial visual patterns in the dataset as shown in the figure 8.
Similarly, both training and validation accuracy curves have a sharp increase in the initial epochs, and the accuracy levels stabilize to above 95% and nearly 99% after approximately the tenth epoch. The fact that the these two curves shows close alignment between them which indicates strong generalization and confirms that the skip mechanism effectively improves gradient flow and feature propagation, preventing vanishing gradient issues and supporting faster-convergence. The confusion matrix also demonstrates the model's robust classification potential. The CNN with Skip Mechanism is able to correctly identify the majority of samples across all three classes; brown spots, healthy, and white scale. Only a few miss-classifications occur, including one brown spot predicted as healthy, one healthy leaf predicted as white scale, and seven white scale samples miss-classified as healthy. There are 396 total samples of which 388 samples are correctly classified which gives us an overall accuracy of approximately 97.98%. These results shows that the addition of skip connections improves the model's feature reuse and learning stability, enabling strong performance comparable to more complex architectures as shown in the figure 9.

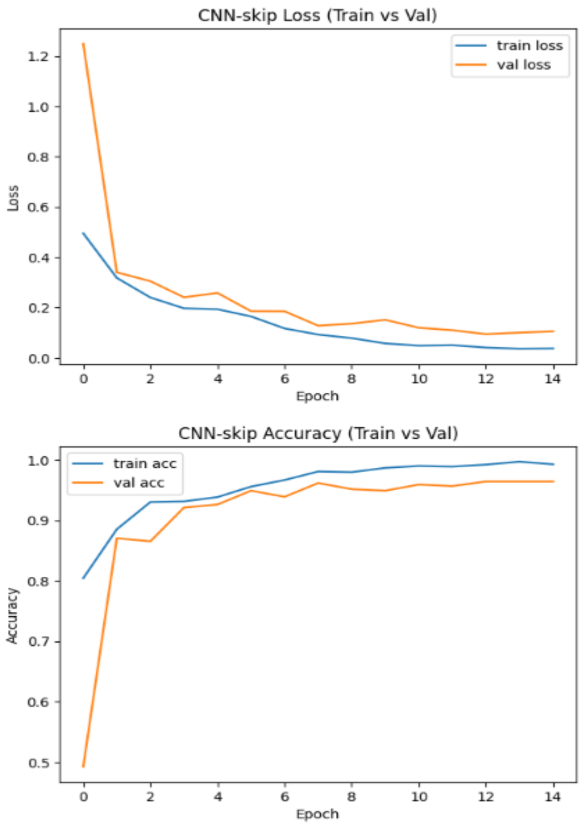

Figure.8 Training – validation loss and accuracy curves for CNN with skip mechanism

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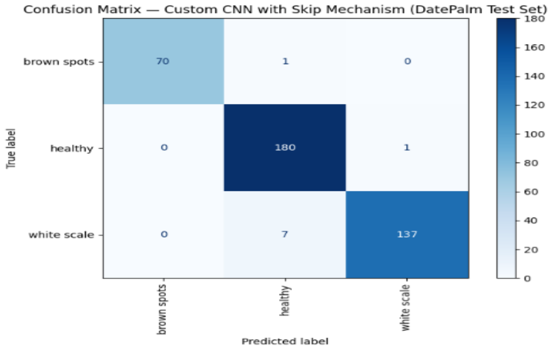

Figure.9 Confusion matrix of CNN with Skip Mechanism

4. **GoogLeNet**

The GoogLeNet [30] graph shows that training loss decreases quickly and then stabilizes near zero, while validation loss remains low with slight fluctuations, indicating strong learning with minor overfitting. The training accuracy quickly reaches 100%, and the validation accuracy peaks around 99.5%, as shown in the figure 10, which confirms that the model is generalized and extract features well. The confusion matrix given in figure 11 of GoogLeNet on the DatePalm test set indicates that the classification accuracy is high in all three classes: brown spots, healthy, and white scale. The model accurately classified all the 'brown spots' samples (71/71) and almost all the 'healthy' and 'white scale' samples, except four sample of 'white scale' there were miss-classified as 'healthy'. This indicates strong discriminator capability, particularly for diseased classes, with minor confusion between visually similar categories.

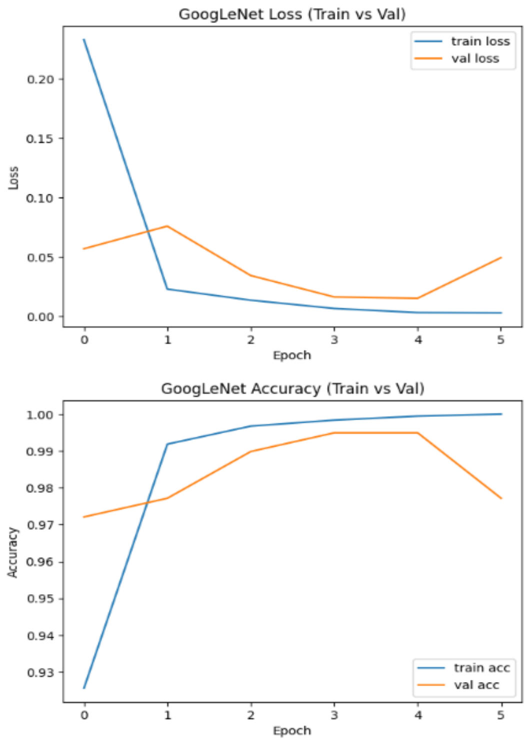

Figure.10 Training – validation loss and accuracy curves for GoogLeNet

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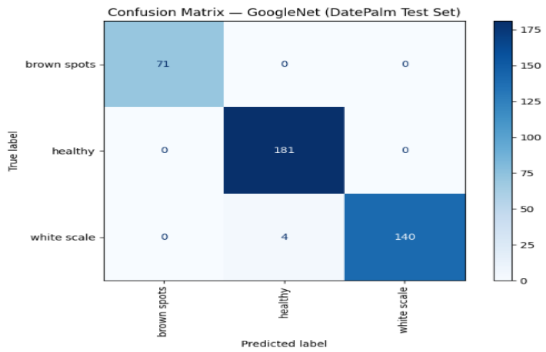

Figure.11 Confusion matrix of GoogleNet

5. **AlexNet**

The AlexNet model [31] demonstrates high learning capability, as the training accuracy increases almost to 100% and validation accuracy increases steadily to approximately 98.8%. Training loss decreases rapidly and goes to zero, and validation loss also declines but remains slightly higher, with minor fluctuations indicating mild over-fitting refere figure 12. Despite this, AlexNet maintains a close relationship between training and validation performance, which affirms good generalization. Its ability to achieve high accuracy with relatively simple architecture highlights its effectiveness for this classification task, though the loss fluctuations that occur indicate that further regularization or earlier stopping would further stabilize the performance.

The confusion matrix also confirms a strong classification on the Date Palm test set. The model has correctly classifies almost all samples across the three classes, namely, brown spots, healthy, and white scale, and only one 'brown spot' is miss-classified as healthy and three samples of 'healthy' class get miss-classified as white scale. Overall, 392 out of 396 samples were predicted successfully which brought an accuracy of about 98.99%. These results confirm that AlexNet can be used to distinguish between diseased and healthy palm leaves with minimal errors between visually similar categories.

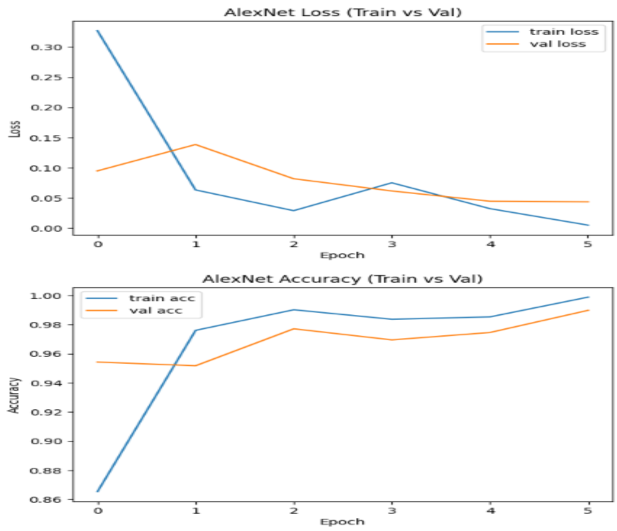

Figure.12 Training – validation loss and accuracy curves for AlexNet

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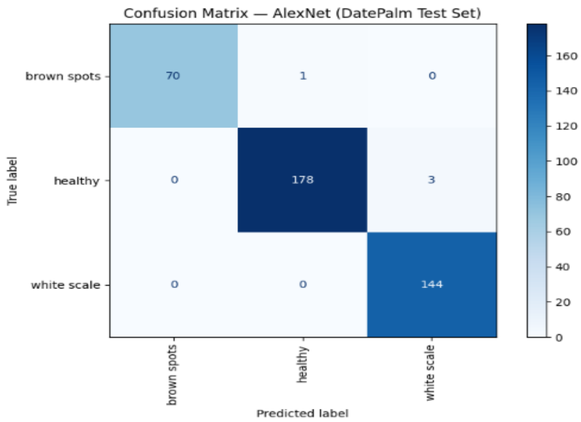

Figure.13 Confusion matrix of AlexNet

6. **Swin Transformer:**

The results shows the potential and sensitivity of transformer-based vision architectures. The baseline model achieved about 37% accuracy, which highlights the challenges of training a transformer-based model on a limited or imbalanced dataset. Nevertheless, after applying extensive data augmentation and unfreezing the model head and complete fine-tuning, the performance drastically improved, with an overall accuracy of about 99%, refer figure 14. The good performance is substantiated by the training and validation curves, there curves show that the losses decline rapidly and become stable at the fifth epoch, whereas the accuracy increases steadily, converging near 100% for both sets. The fact that the values of two curves aligned closely and indicates excellent generalization with minimum over-fitting.

Further, these findings are supported by the confusion matrix, shown in figure 15 as nearly all the samples across the three classes (brown spots, healthy, and white scale) were correctly classified by Swin Transformer [32]. There were only two samples that were miss-classified one brown spot as healthy and one white scale as healthy. This results in a total classification accuracy of 99.49%, affirming that Swin-Transformer accurately registers fine-grained visual distinctions in the dataset.

These findings promote the usefulness of transfer learning methods like augmentation, layer freezing, and tuning the learning rate when adopting transformer-based models to small, domain-specific datasets. The model's performance shows that it has high representational capability and resilience for the task of disease detection in date palm images.

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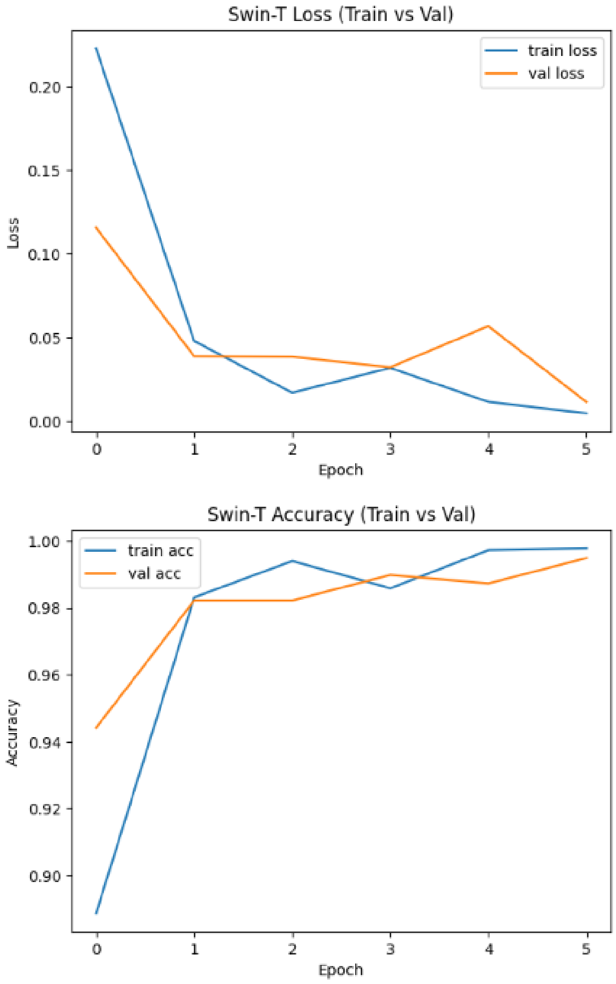

Figure.14 Training – validation loss and accuracy curves for Swin Transformer

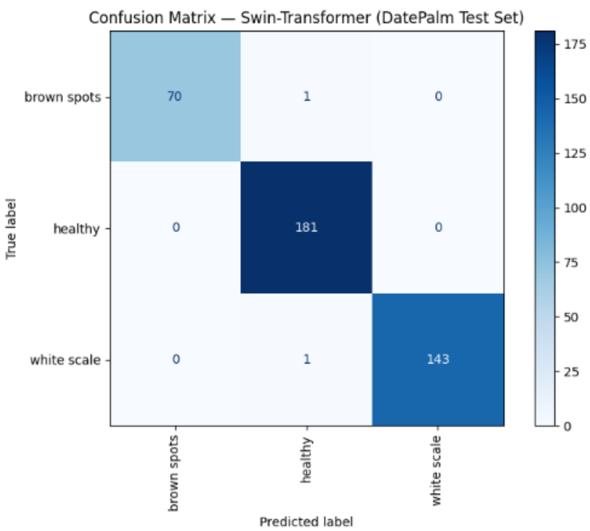

Figure.15 Confusion matrix of Swin-Transformer

7. ViT-B/16

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ViT-B/16 model [33] has an excellent convergence and high generalization. The training loss decreases drastically during the first epoch and tends towards reaching nearly zero in the fifth epoch, whereas the validation loss is steadily decreasing with minor fluctuations, which signifies a stable and effective learning process. Both training and validation accuracies rise rapidly and stabilize close to 100%, confirming that the model efficiently learns and generalizes the discriminative features of the date palm leaves. The small fluctuations in validation loss during initial epochs reflect brief adaptation instability as adaptations of transformer-based models, but the overall trends demonstrate that the model is well-regularized and finely tuned. The confusion matrix additionally confirms the high classification performance of ViT-B/16 on the DatePalm test set. The model correctly classifies almost all samples across the three classes; brown spots, healthy, and white scale and misclassifies only three samples (one brown spot as healthy, one healthy as brown spot, and one white scale as healthy). Out of 396 test samples, 393 were correctly predicted, resulting in an overall accuracy of approximately 99.24%. These results confirm that ViT-B/16 not only converges efficiently but also attain a high level of accuracy for predictions across all classes, which demonstrate its robustness and adaptability to be scaled to fine-grained disease detection in date palm imagery. The table 1shows model performance.

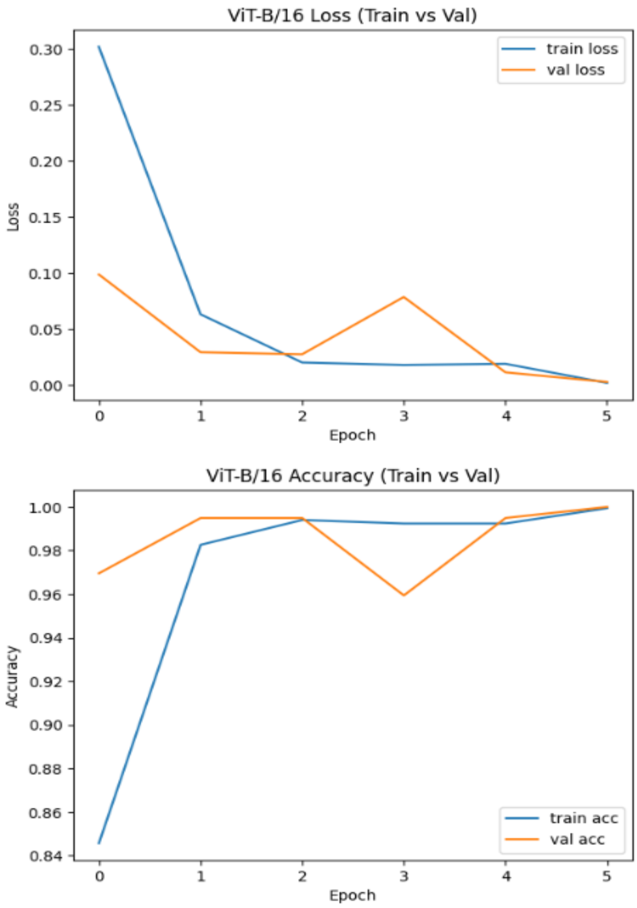

Figure.16 Training, validation loss and accuracy curves for ViT

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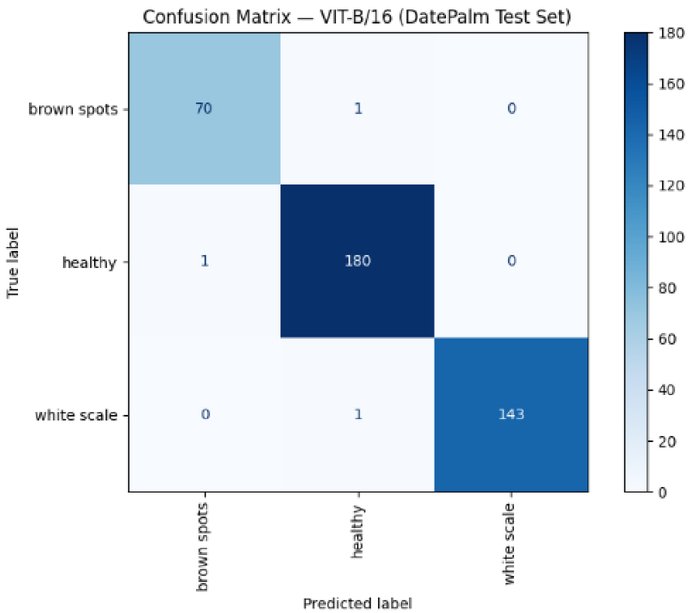

Figure.17 Confusion matrix of ViT-B/16

Table 1: Model Performance on Date Plam Disease Classification

Models	**Epochs**	**Accuracies**	**Loss:**	**Precision**	**Recall**	**F1_score**
Custom CNN with 3 layers	15	Train: 97.34% validation: 94.92% Test: 97.98%	Train: 0.132 validation: 0.177 Test: 0.150	0.9851	0.9796	0.9821
Custom CNN with 4 layers	15	Train: 99.08% validation: 95.94% Test: 97.73%	Train: 0.042 validation: 0.122 Test: 0.0864	0.9810	0.9711	0.9757
CNN with attention mechanism	15	Train: 97.94% validation: 95.69% Test: 97.73%	Train: 0.107 validation: 0.157 Test: 0.122	0.9786	0.9534	0.9760

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CNN with Skip Mechanism	15	Train: 99.29% validation: 96.45% Test: 97.47%	Train: 0.037 validation: 0.1050 Test: 0.0709	0.9817	0.9749	0.9780
AlexNet	6	Train: 99.8 % validation: 98.9% Test: 98.74%	Train: 0.0052 validation: 0.0438 Test: 0.057	0.9865	0.9818	0.9840
GoogleNet	6	Train: 99.9% validation: 97.7% Test: 99.75%	Train: 0.0030 validation: 0.0494 Test: 0.0178	0.9982	0.9977	0.9979
VIT	6	Train: 99.95% validation: 99.49% Test: 99.49%	Train: 0.0023 validation: 0.0031 Test: 0.0151	0.9964	0.9930	0.9946
Swin-Transformer	6	Train: 99.78% validation: 99.49% Test: 98.99%	Train: 0.0046 validation: 0.0113 Test: 0.0404	0.9935	0.9930	0.9932

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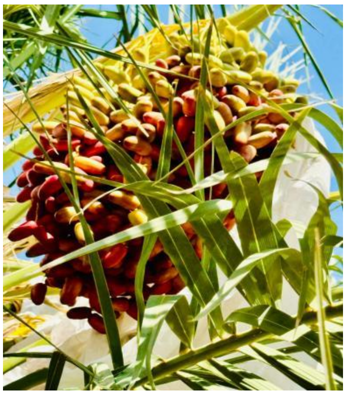
4. Discussion

In this paper, deep learning models have been implemented on the dates crop dataset to investigate possible diseases that may infect the whole crop and impact the total yield of the entire cycle. The swin-transformer achieves very good accuracy as compared to other models.The other models also perform well and urge the strong need to implement AI-enabled solutions for date farming in Saudi Arabia. The following samples in the figure below show the dates trees in the Madinah region of the Saudi Arabia where the proposed method will be implemented in the next phase.



5. Conclusion and Future Direction

The paper proposes a deep learning model-based implementation to detect disease in date farming. The work introduces how to incorporate AI-enabled solutions to transform date farming in the agriculture sector. By transforming agriculture's traditional farming practices into the new and modern technology-orientated framework, This paper helps in improving the yield and boosting the country's economy and it will eventually reduce food scarcity.

References:

1. T. van Klompenburg, A. Kassahun, and C. Catal, "Crop Yield Prediction Using Machine Learning: A Systematic Literature Review," *Computers and Electronics in Agriculture*, vol. 177, p. 105709, 2020
2. S. P. Mohanty, D. P. Hughes, and M. Salathé, "Using Deep Learning for Image-Based Plant Disease Detection," *Frontiers in Plant Science*, vol. 7, p. 1419, 2016
3. M. A. Al-Garadi, A. Mohamed, A. Al-Ali, X. Du, I. Guizani, and M. Guizani, "A Survey of Machine and Deep Learning Methods for Internet of Things (IoT) Security," *IEEE Communications Surveys & Tutorials*, vol. 22, no. 3, pp. 1646-1685, thirdquarter 2020
4. D. C. Rose and J. Chilvers, "Agriculture 4.0: Broadening Responsible Innovation in an Era of Smart Farming," *Frontiers in Sustainable Food Systems*, vol. 2, p. 87, 2018
5. Krueger, R.R. Date Palm (Phoenix dactylifera L.) Biology and Utilization. In The Date Palm Genome; Springer: Cham, Switzerland, 2021; Volume 1, pp. 3–28.
6. Saboori, S.; Noormohammadi, Z.; Sheidai, M.; Marashi, S. Insight into date palm diversity: Genetic and morphological investigations. Plant Mol. Biol. Rep. 2021, 39, 137–145

7. Abdelmonem, A.; Rasmy, M. Major diseases of date palm and their control. Commun. Inst. For. Bohem 2007, 23, 9–23.
8. Percival, G.C.; Graham, S. The potential of resistance inducers and synthetic fungicide combinations for management of foliar diseases of nursery stock. Crop Protect. 2021, 145, 105636. [CrossRef]
9. Prasertsan, P.; Nutongkaew, T.; Leamdum, C.; Suyotha, W.; Boukaew, S. Direct biotransformation of oil palm frond juice to ethanol and acetic acid by simultaneous fermentation of co-cultures and the efficacy of its culture filtrate as an antifungal agent against black seed rot disease. Biomass Convers. Biorefin. 2021, 1–10. [CrossRef]
10. (https://www.fao.org/faostat/en/#data/QC last accessed 10 December 2021)
11. Abdalla, M.Y., G.H. Ibrahim, A.A. Al-Mihanna and A.A. Al-Rokibah, 2001. Brown leaf spot of date palm in Saudi Arabia and the influence of leaf Epicuticular wax on disease severity. J. Adv. Agric. Res., 6: 585-593
12. Al-Shayaa M. S., Baig M. B. & Straquadine G. S. 2012 Agricultural extension in the Kingdom of Saudi Arabia: difficult present and demanding future. The Journal of Animal & Plant Sciences 22 (1), 239–246.
13. Al-Amoud A. I., Mohammad F. S., Al-Hamed S. A. & Al-Abdulkader A. M. 2012 Reference evapotranspiration and date palm water use in the kingdom of Saudi Arabia. International Research Journal of Agricultural Science and Soil Science 2 (4), 155–169. Retrieved from http://www.interesjournals.org/IRJAS
14. Al-Abbad A., Al-Jamal M., Al-Elaiw Z., Al-Shreed F. & Belaifa H. 2011 A study on the economic feasibility of date palm cultivation in the Al-Hassa Oasis of Saudi Arabia. Journal of Development and Agricultural Economics 3 (9), 463–468.
15. Almadini A. M., Ismail A. I. H. & Ameen F. A. 2021 Assessment of farmers practices to date palm soil fertilization and its impact on productivity at Al-Hassa oasis of KSA. Saudi Journal of Biological Sciences 28 (2), 1451–1458. https://doi.org/10.1016/j.sjbs.2020.11.084.
16. Fathi,A.&Al-Kahtani,M.2009WaterQualityandPlanktonicCommunitiesinAl-KhadoudSpring,Al-Hassa,SaudiArabia.American JournalofEnvironmentalSciences5(3),434–443.
17. Al-Zarah,A.I.2011ElementalcompositionofgroundwaterandspringwatersinAl-AhsaOasis,EasternRegionSaudiArabia.Trendsin AppliedSciencesResearch6(1),1.
18. AlTokhais,A.S.&Rausch,R.2008ThehydrogeologyofAlHassaSprings.In:The3rdInternationalConferenceonWaterResourcesand AridEnvironments,November2008.
19. Almadini,A.M.,Ismail,A.I.H.&Ameen,F.A.2021 Assessment of farmers practices to date palms oil fertilization and its impacton productivityatAl-HassaoasisofKSA.Saudi Journal of Biological Sciences 28(2),1451–1458. https://doi.org/10.1016/j.sjbs.2020.11.084.
20. Al-Khalifah,N.S.2012First Arab Palm Conference on the Development of Date Palm and Dates Sector in the Arab World. Emir.J.FoodAgric24(5).
21. Ashraf,Z. & Hamdi-asfahani, Z. 2011 Date and date processing : a review. Food Reviews International 27,101–133.
22. Alkolibi F. M. 2002 Possible effects of global warming on agriculture and water resources in Saudi Arabia: impacts and responses. Climatic Change 54 (1–2), 225–245. https://doi.org/10.1023/A:1015777403153.

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23. Mohan Jain S. 2012a Date palm biotechnology: current status and prospective-an overview. Emirates Journal of Food and Agriculture 24 (5), 386-399. https://ejfa.me/index.php/journal/article/view/923.
24. Mohan Jain S. 2012b In vitro mutagenesis for improving date palm (Phoenix dactylifera L.). Emirates Journal of Food and Agriculture 24 (5), 400-407. https://www.ejfa.me/index.php/journal/article/view/927.
25. Bahn R. A., Yehya A. A. K. & Zurayk R. 2021 Digitalization for sustainable agri-food systems: potential, status, and risks for the Mena region. Sustainability (Switzerland) 13 (6), 1–24.
26. Thornton P., Dinesh D., Cramer L., Loboguerrero A. M. & Campbell B. 2018 Agriculture in a changing climate: keeping our cool in the face of the hothouse. Outlook on Agriculture 47 (4), 283–290.
27. Lindblom J., Lundstro C. & Jonsson A. 2017 Promoting Sustainable Intensification in Precision Agriculture : Review of Decision Support Systems Development and Strategies. pp. 309–331. https://doi.org/10.1007/s11119-016-9491-4.
28. https://www.kaggle.com/datasets/hadjerhamaidi/date-palm-data/data
29. O'shea, Keiron, and Ryan Nash. "An introduction to convolutional neural networks." arXiv preprint arXiv:1511.08458 (2015).
30. Szegedy, Christian, et al. "Going deeper with convolutions." Proceedings of the IEEE conference on computer vision and pattern recognition. 2015.
31. L. Xiao, Q. Yan and S. Deng, "Scene classification with improved AlexNet model," 2017 12th International Conference on Intelligent Systems and Knowledge Engineering (ISKE), Nanjing, China, 2017, pp. 1-6, doi: 10.1109/ISKE.2017.8258820.
32. Liu, Ze, et al. "Swin transformer: Hierarchical vision transformer using shifted windows." Proceedings of the IEEE/CVF international conference on computer vision. 2021.
33. Dosovitskiy, Alexey. "An image is worth 16x16 words: Transformers for image recognition at scale." arXiv preprint arXiv:2010.11929 (2020).