AI-Driven Date Fruit Classification via Transfer Learning in Smart Agriculture

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Digital technologies, including the Internet of Things (IoT) and deep learning, are increasingly propelling smart agriculture. A vital aspect is the automated classification of objects for crop assessment and quality control. This study addresses the practical challenge of limited labeled data by investigating the efficacy of Transfer Learning (TL) for multi-grade classification of date fruit varieties. We conduct a rigorous comparative analysis using three popular pre-trained Convolutional Neural Network (CNN) architectures—VGG16, ResNet50, and Inception V3—benchmarked against traditional CNN methodologies. The experimental setup utilizes the TU-DG dataset, which comprises 3,383 images and is partitioned into a 70% training, 20% validation, and 10% testing split. Models are fine-tuned using the Adam optimizer and evaluated based on accuracy, precision, F1-score, and recall. Our analysis demonstrates that TL significantly surpasses traditional methodologies, which achieved an accuracy of 98%. Specifically, the VGG16 and Inception V3 models achieved a test accuracy, precision, recall, and F1-score of 100%, while ResNet50 achieved 99.85% across all metrics. These results validate the TL approach's ability to achieve robust results and establish a new benchmark for automated date fruit grading.

Povzetek: Prispevek predstavlja uporabo prenosa učenja za avtomatsko klasifikacijo sort in kakovostnih razredov datljev na podatkovni zbirki TU-DG ter primerja modele VGG16, ResNet50 in InceptionV3. Izvirni doprinos je v sistematični primerjavi predhodno naučenih CNN-arhitektur za omejen kmetijski slikovni nabor, s čimer avtorica pokaže praktično vrednost strojnega učenja za pametno kmetijstvo.

1 Introduction

Smart agriculture has emerged as a pivotal solution to address global food security challenges, particularly as the world population continues to grow. Its primary objective is to enhance crop yields, operational efficiency, and economic viability through the integration of advanced technologies such as the Internet of Things (IoT), Machine Learning (ML), Deep Learning (DL), and big data analytics. The urgency to incorporate such technologies into farming practices is unprecedented, driven by the need to ensure sustainable food production and environmental conservation [27].

Remote sensing tools, including satellite imagery and unmanned aerial vehicles (UAVs), provide powerful capabilities for monitoring crop health and identifying threats such as disease outbreaks, drought stress, and pest infestations. These technologies enable targeted interventions and more efficient resource management. Furthermore, automated plant and fruit recognition, supported by Convolutional Neural Networks (CNNs), has demonstrated strong potential for precise classification and feature extraction from images [1], facilitating faster and more accurate agricultural decision-making. Automated fruit recognition can significantly improve efficiency across the agricultural supply chain, from orchards to processing facilities and retail.

Advanced intelligent systems also allow early detection of plant diseases, one of the most critical challenges in modern agriculture, which permits timely interventions that preserve crop health and reduce losses [12]. IoT technologies hold particular value in harsh environments, such as the Arab Gulf, by enabling real-time monitoring of soil moisture, temperature, humidity, and light intensity [14, 7]. The integration of ML algorithms with IoT infrastructures facilitates the processing of large datasets from multiple sources, which include IoT devices, drones, and satellites, to generate predictive models for crop yield forecasting based on environmental factors. Additionally, AI-powered systems are revolutionizing routine agricultural tasks through autonomous operations, such as weeding and harvesting [36].

In light of these technological advancements, there is a pressing need for comprehensive studies that review the integration of ML, IoT, and AI in agriculture and propose novel approaches for real-world applications. This study advances the field of smart agriculture by focusing on the practical deployment challenges of classification systems. Our key contributions are: Validating Transfer Learning for Resource Efficiency:

1. We provide empirical evidence of the high efficacy of Transfer Learning (TL) for date fruit classification,

achieving 85% accuracy with limited data, which is crucial for resource-constrained agricultural settings.

2. Benchmarking State-of-the-Art CNNs for Date Fruit: We conduct a direct, comparative analysis of established pre-trained CNNs (VGG16, ResNet50, Xception) to quantify the practical performance gain of TL over traditional methods for date fruit grading and quality assessment.

3. Addressing the Agricultural TL Literature Gap: We highlight and fill a significant gap in the literature regarding the systematic and validated application of Transfer Learning in real-world agricultural classification tasks, offering a refined methodology for crop assessment.

The remainder of this paper is structured as follows: Section 2 presents the basic concepts of CNNs, TL, and state-of-the-art CNN models. Section 3 reviews IoT and data analytics applications in agriculture. Section 4 highlights smart agriculture systems from the literature. Section 5 discusses key challenges in applying these technologies. Section 6 presents a case study with experimental results, followed by conclusions and future work in Section 7.

2 Foundational overview of convolutional neural networks (CNNs) and transfer learning (TL)

This section provides a foundational overview of Convolutional Neural Networks (CNNs), Transfer Learning (TL), and pretrained CNN architectures relevant to this study.

2.1 Convolutional neural networks (CNNs)

Deep Learning (DL) methods have become essential for analyzing large-scale unprocessed datasets, with CNNs playing a central role in image classification. CNNs comprise an input layer, multiple convolutional layers for feature extraction, pooling layers for dimensionality reduction, and fully connected layers for classification. Convolutional layers apply filters to generate feature maps, while pooling layers (e.g., max pooling) retain the most important information. Stacking multiple convolutional and pooling layers enables deeper feature extraction, thereby improving the network's capacity to identify complex patterns [37].

2.2 Transfer learning (TL)

TL leverages pretrained models and their learned weights to address new tasks, thereby reducing the need for extensive training and large labeled datasets. TL has shown promising results in applying architectures such as ResNet50, DenseNet, and VGG16 to image classification [30], [35].

2.2.1 VGG16

Developed by Oxford's Visual Geometry Group, VGG16 [30] is a 16-layer CNN trained on over one million images from ImageNet [31]. It utilizes stacked 3x3 convolutional filters and max pooling layers, culminating in two fully connected layers of 4096 nodes and a 1000-class SoftMax classifier.

2.2.2 ResNet50

ResNet50 employs residual learning via shortcut connections to address the issues of vanishing and exploding gradients, thereby enabling deeper network training without accuracy degradation [32]. Its architecture is widely used in TL tasks.

2.2.3 InceptionV3

InceptionV3 is a 48-layer network capable of classifying 1000 categories. It employs parallel convolutions with different filter sizes (1x1, 3x3, 5x5) to efficiently capture multi-scale features.

3 Modern technologies and IoT applications in agriculture

The Internet of Things (IoT) integrates agricultural devices, sensors, and platforms to facilitate data collection and enable real-time decision-making [25]. The applications of IoT within the farming sector are multifaceted and include:

3.1 Enhancing agricultural efficiency and safety

Agricultural technologies leverage diverse sensor networks to improve productivity and operational security. Key deployments include soil moisture sensors, atmospheric monitors, and heavy metal detectors, which provide the granular data necessary for AI-driven decision-making [9, 38].

3.1.1 Smart irrigation

IoT-based irrigation systems integrate satellite positioning with automated hardware to optimize water distribution. These systems significantly reduce water and electricity consumption while ensuring precise timing for irrigation schedules, which is vital for date palm cultivation [9].

3.1.2 Smart safety and crop protection

– Operational Safety: Contemporary agricultural safety systems utilize IoT technology for the continuous surveillance of storage and processing facilities. By identifying hazards such as electrical faults or environmental fluctuations in real-time, these systems safeguard both the workforce and the harvested products

[38, 3]. Advanced control systems further maintain optimal storage conditions by automatically adjusting temperature and humidity.

– AI-Driven Protection: Modern management systems integrate predictive analytics and computer vision for early threat detection [24]. AI-powered image recognition facilitates the identification of pests and diseases at early stages, allowing for proactive interventions that preserve crop health and maximize yield quality [24, 12].

4 Modern technologies and IoT applications in smart agriculture: A review

The rapid integration of Internet of Things (IoT), Artificial Intelligence (AI), and Deep Learning (DL) technologies is fundamentally transforming agriculture into a more precise, efficient, and sustainable enterprise. This section synthesizes the literature from Sections 3 and 4, grouping key findings under thematic subtopics to provide a coherent overview of modern smart agriculture systems and their applications.

4.1 Integration of IoT, cloud computing, and wireless sensor networks

The foundation of modern smart agriculture lies in the interconnected nature of IoT infrastructure. IoT integrates agricultural devices, sensors, and platforms to enable data collection and real-time decision-making. A study by [15] has focused on developing robust system architectures to manage this influx of data. For instance, one proposed precision agriculture system uses a three-layer architecture: the first layer gathers data from equipment and sensors, the second employs an IoT network to connect peripherals, and the third handles processing and storage. Another innovative system leverages Wireless Sensor Network (WSN) technology and the Message Queuing Telemetry Transport (MQTT) protocol to efficiently collect data from plants, particularly in greenhouses and variable weather conditions5. This WSN/MQTT approach proved highly efficient, transmitting data over 4G networks at low bandwidths (0.02 to 1.65 kbps), [6]. In a notable advancement for precision agriculture, [22] developed an innovative smart greenhouse monitoring system aimed at enhancing crop quality. This novel prototype creates an optimized artificial environment within greenhouses by regulating crucial factors such as water irrigation, ventilation, light intensity, and CO2 concentration. The system design incorporates a cost-effective Wi-Fi module, specifically NodeMCU V3, and features an Android mobile application that keeps farmers informed through timely notifications. This integration of affordable technology and user-friendly interfaces represents a significant step toward making advanced agricultural monitoring accessible to a wider range of farmers. Phenonet, an innovative open source platform developed on OpenIOT technology, exemplifies the cutting-edge application of digital technologies in agriculture. Introduced by [13], this smart farming solution addresses key challenges in precision agriculture while highlighting the transformative potential of such applications. The Phenonets robust architecture facilitates comprehensive data management, encompassing collection, validation, processing, and storage capabilities. This integrated approach enables precise semantic queries and supports detailed experimental analysis, thereby enhancing decision-making in agricultural practices. By demonstrating the effectiveness of the strategy, the research underscores the vital role of digital innovation in advancing modern farming techniques and improving overall agricultural efficiency.

A comprehensive systematic review of 56 studies on Artificial Vision Systems for Fruit Inspection and Classification (2015–2024) established the foundational landscape [16]. The review found that applications span orchards, industrial processing lines, and retail, with RGB cameras dominating image acquisition ($\approx$ 84%), making simple visual systems the prevailing standard. While traditional methods like Otsu and Sobel are still used, deep learning models (VGG, ResNet, YOLO) have become the superior methodology, often enhanced through transfer learning. The primary challenges identified are lighting variability, dataset standardization, and the growing demand for lightweight, real-time deployment solutions. To address the need for lightweight and performant models, recent studies focus on optimizing deep learning architectures: Attention-Enhanced Detection: Swapno et al. [17] introduced CA-YOLOv9 (YOLOv9 with Coordinate Attention) for precise segmentation in the medical domain. Although applied to renal pathology, the approach validates that incorporating spatially-aware attention mechanisms can significantly boost detection accuracy (mask mAP@50 of 0.957) with minimal computational overhead, a principle transferable to high-speed agricultural inspection tasks. Lightweight Classification: A study comparing deep learning models for fruit classification introduced an optimized MobileNetV3 architecture [18]. The key modification was replacing the ReLU6 activation function with the Hard-Swish (H-Swish) function. This optimization improves model efficiency and maintains high accuracy (e.g., 99.2% on Fruit360), confirming the effectiveness of using computationally simpler activation functions for models intended for mobile or edge deployment.

The study [19] presents an overview of the Internet of Things (IoT) in agriculture, emphasizing its integration with artificial intelligence (AI) and web services to enhance efficiency, productivity, and sustainability. It highlights the role of wireless sensor networks, RFID, and cloud computing in enabling real-time monitoring, data analytics, and remote control of agricultural systems. The integration of these technologies supports optimized resource management, reduced waste, and improved crop yields, while addressing challenges such as data privacy, high implementation costs, and technical expertise requirements. The work also points to emerging research in 5G connectivity, AI-driven automation, and decentralized networks as key enablers for the future of smart and scalable agriculture. The study conducted a systematic literature review (SLR) to examine the integration of image classification techniques within IoT-based smart agriculture platforms [20]. It identified five main application domains: disease and pest detection, crop growth and health monitoring, irrigation and crop protection management, intrusion detection, and fruit and plant counting. The review revealed three primary strategies for image processing: edge computing, which enables real-time decision-making but incurs higher implementation costs; cloud computing, which allows high-resolution image analysis but depends on stable connectivity; and hybrid approaches, combining both to balance performance and infrastructure needs. Overall, the findings underscore that disease and pest detection dominate current research, while hybrid and low-cost IoT architectures remain experimental but promising for future smart farming innovations. Hasan et al. developed a blockchain- and IoT-based framework to ensure traceability, transparency, and trust across the agricultural supply chain [21]. The proposed system continuously monitors soil, air, and crop health through IoT sensors and records all data immutably on a permissioned Ethereum blockchain using smart contracts. It integrates organic, non-GMO, and Global GAP certifications, allowing consumers to verify food authenticity via QR codes. The framework eliminates fraudulent labeling and enhances accountability among farmers, certifying bodies, and retailers. Testing results showed efficient operation with low computational cost, while security analysis using Slither confirmed resilience against vulnerabilities. The study demonstrates that combining blockchain with IoT can significantly strengthen sustainable food certification and consumer trust through real-time, tamper-proof data provenance. Table 1 effectively illustrates the diversity of approaches in smart agriculture and IoT applications, showing how different combinations of technologies can be applied to solve various agricultural challenges. A variety of sensors and platforms have been used, including wireless sensors, Wi-Fi modules, and specialized platforms such as OpenIoT Phenonet.

5 IoT and data analytics in smart agriculture: challenges and future directions

5.1 Human behavior challenges

The integration of IoT in agriculture presents both opportunities and challenges, particularly in developing rural areas. The research by [11] explored how IoT technologies can improve sustainable farming practices and create new job opportunities in rural agricultural sectors. Their study also examined farmers' acceptance of smart farming technologies, aiming to improve rural living standards through technological adoption. Complementing this, [8] focused on the potential of IoT to address agricultural waste management. They emphasized the critical role of agriculture in human civilization and the pressing need to conserve resources. By proposing IoT-based monitoring and control systems, particularly for irrigation optimization, their research suggests that smart technologies can significantly reduce water waste. This approach not only conserves resources but also aims to shift long-standing human behaviors away from traditional, less efficient farming practices. Together, these studies highlight the transformative potential of IoTs in agriculture, from improving rural livelihoods to promoting more sustainable resource management.

5.2 Technical challenges

The integration of IoT in agriculture presents both opportunities and challenges for modern farming. As highlighted by [23], a key benefit is the ability to provide timely guidance to farmers, helping them avoid crises and manage diseases effectively. This approach relies on creating a comprehensive knowledge database using smart objects deployed across various farms. By analyzing these data, potential obstacles can be identified, allowing a central guidance system to assist farmers in making informed decisions. For example, such systems can accurately calculate irrigation needs based on weather and soil conditions or optimize the application of chemicals and medicines, ultimately boosting overall farm productivity. However, the implementation of IoT in agriculture faces several hurdles, as outlined by [26]. These challenges include securing adequate funding, managing development costs, addressing standardization issues, optimizing power consumption, considering environmental impacts, and ensuring data security. Despite these obstacles, the rapid advancement of smart farming technologies, including sensors and virtual systems, continues to drive innovation in the field. [10] further elaborates on the technical challenges of implementing IoT in smart agriculture. These range from selecting appropriate hardware components such as sensors and communication channels to developing sophisticated data analysis systems and control algorithms. Maintenance of these systems in remote and harsh environments poses additional difficulties. Furthermore, ensuring reliable network connectivity for farmers to access plant information via mobile devices remains a critical concern. Perhaps most importantly, the cybersecurity risks associated with these systems cannot be overlooked, as unauthorized access could potentially cause significant damage to crops and farming operations.

Table 1: Comparative analysis of deep learning and IoT systems in agriculture

Ref.	Primary Technology	Application / Sensor	Model / Dataset	Key Performance / Results
[17]	Deep Learning	Medical / Image sensors	CSA-YOLO / Medical imaging	mAP@50 = 0.957; outperformed YOLOv8 by 3.59%.
[18]	Deep Learning	Fruit Datasets	MobileNetV3 (Hard-Swish)	99.2% accuracy on Fruit360; 89.3% on real-world data.
[33]	Classical CNN	Dates Grading	Novel Date Dataset	98% Accuracy (Comparative Baseline).
[6]	IoT / Cloud	Wireless sensors	Greenhouse monitoring	Effective data acquisition in unpredictable weather.
[20]	IoT-enabled Image Classification	Cameras	Cloud, Edge, and Hybrid platforms	Identified disease detection and growth monitoring as key domains.
[21]	IoT & Blockchain	Soil, pH, nutrient sensors	Permissioned Ethereum / Smart Contracts	Enhanced food traceability and sustainability in supply chains.

6 Use case: dates classification

6.1 Proposed approach

The proposed architecture utilizes pre-trained convolutional bases where the original fully connected layers are removed and replaced with a specialized classification head. As detailed in Figure 1, the process includes:

- Preprocessing Block: Images are resized to 224×224 (VGG16 and ResNet50) or 299×299 (Inception V3).
- Normalization is applied using ImageNet mean and standard deviation values to align input data with pre-trained weights.
- Data Augmentation: To simulate agricultural variability, random horizontal flips, rotations up to 10°, and 20% zoom adjustments are performed.
- Custom TL Layers: The pre-trained base is followed by a Global Average Pooling layer to reduce dimensionality, a Dense layer with 1024 neurons (ReLU activation), and a Dropout layer (0.5) to prevent overfitting.
- Output Head: A final Sigmoid activation layer is used with Binary Cross-Entropy (BCE) loss to facilitate independent confidence scoring for date varieties and grades.

6.2 Dataset

The Taibah University-Dates Grading (TU-DG) dataset comprises three varieties of dates: Ajwa, Mabroom, and Sukkary, each represented across multiple grades. Figure 2 provides sample images from the dataset. The TU-DG dataset is publicly accessible via IEEE Dataport. [1].

Table 2 shows the number of images in each type of date for all grades in the TU-DG dataset. The dataset comprises

Table 2: Types and grades breakdown for dates dataset

Date type	Grade 1	Grade 2	Grade 3	Total
Ajwah	300	345	492	1137
Mabroom	300	500	496	1296
Sukkary	492	458	0	950

3, 383 images in total, covering three distinct Date Types and three corresponding Quality Grades (Grade 1, Grade 2, and Grade 3).

6.3 Experiments methodology

6.3.1 Hardware specifications

All experiments were implemented using the TensorFlow/Keras framework. Training was performed on a workstation equipped with an NVIDIA RTX 3090 GPU. The total computational time for fine-tuning each architecture ranged from 45 to 75 minutes, depending on the model depth.

6.3.2 Preprocessing and augmentation pipeline

To enhance model robustness against environmental noise, the following pipeline was implemented:

- Resizing: Images were resized to match pre-trained architecture requirements (224×224 or 299×299).

[1] `https://ieee-dataport.org/open-access/tu-dg-dataset-date-grading`

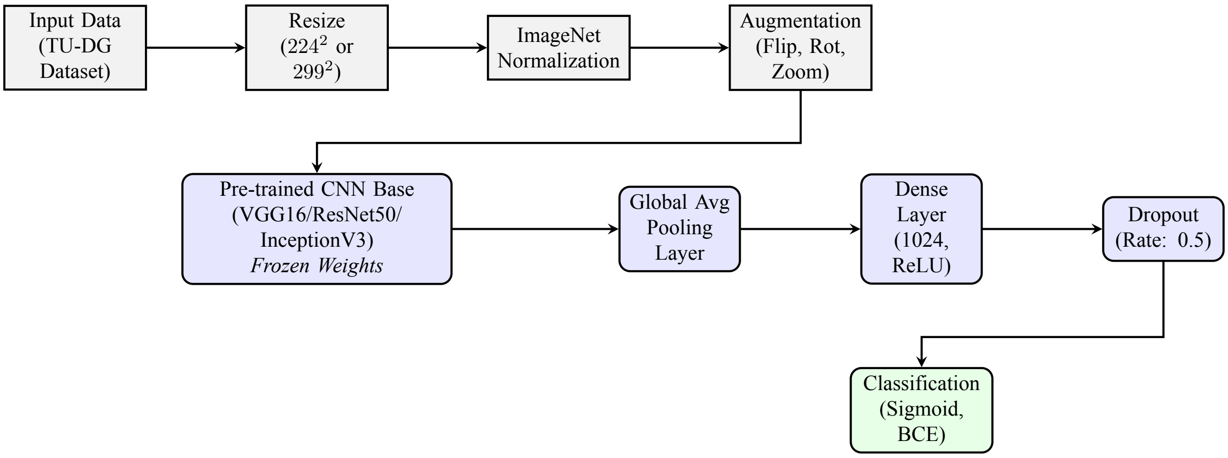


Figure 1: Detailed architectural flow illustrating the Transfer Learning pipeline, including specific pre-processing blocks, model-specific input dimensions, and custom layers added for multi-grade classification.

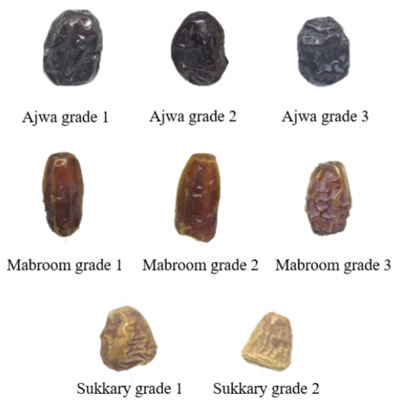


Figure 2: Samples of the dates dataset

- Normalization: Pixel values were scaled to $[0, 1]$ and normalized using ImageNet mean and standard deviation.

- Augmentation: To mitigate overfitting, training data underwent random horizontal flips, rotations up to $10°$, and 20% zoom ranges.

- Specific adjustments were made to brightness and contrast to simulate agricultural lighting fluctuations.

6.3.3 Loss function and stratification

Data split followed a 70/20/10 ratio using stratified logic to maintain class distribution. Although the task is multi-class, we employed Binary Cross-Entropy loss and a Sigmoid activation function. This was chosen to facilitate independent confidence scoring for the three varieties and quality grades, and performance was validated using five-fold cross-validation to ensure statistical reliability.
To ensure the statistical reliability of the performance metrics and to mitigate the risks of overfitting or data leakage, we implemented a stratified five-fold cross-validation procedure.

- Data Partitioning: The total dataset of 3,383 images was partitioned into five distinct, equally sized folds.

- Stratification: Each fold was stratified to maintain the original proportion of date types (Ajwa, Mabroom, Sukkary) and quality grades.

- Iterative Training: The models were trained five times. In each iteration, four folds were used for training and validation (90%), while the remaining fold (10%) served as the independent test set.

- Statistical Reporting: Final results are reported as the mean $\pm$ standard deviation across all five iterations to provide transparency regarding performance variance.

The proposed system's evaluation is based on the following criteria: Accuracy is defined as the ratio of correctly predicted outcomes to the total predictions, expressed as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}. \tag{1}$$

Precision indicates the proportion of positive predictions that are correct and is calculated by dividing the number of true positives by all positive predictions as follows:

$$Precision = \frac{TP}{TP + FP}. \tag{2}$$

Recall reflects the model's ability to detect all potential positives; it is calculated by dividing the true positives by the sum of actual positives as:

$$Recall = \frac{TP}{TP + FN}. \tag{3}$$

The F1 score is defined as the weighted average of recall and precision, calculated as follows:

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}. \quad (4)$$

where

- True Positive (TP): The true category is positive; the predicted category is positive.
- True Negative (TN): The true category is negative; the predicted category is negative.
- False Positive (FP): The true category is negative; the predicted category is positive.
- False Negative (FN): The true category is positive; the predicted category is negative.

6.4 Experimental results

The performance metrics for the three fine-tuned CNN models are summarized in Table 3. VGG16 and Inception V3 achieved perfect test accuracy (100%), while ResNet50 reached 99.85%. These results demonstrate the high efficacy of Transfer Learning in date fruit classification. The confusion matrices in Figure 3 further detail the per-category performance, illustrating the models' precision in distinguishing between varieties and quality grades. The VGG16 and Inception architectures demonstrated exceptional performance, both achieving perfect accuracy at 100%. In contrast, the ResNet50 model, while still highly effective, slightly underperformed compared to its counterparts, which achieves a 99.85% accuracy rate. These findings not only highlight the effectiveness of our approach, but also provide valuable information on the relative strengths of different CNN architectures for date fruit classification tasks. The performance metrics and confusion matrices for the three architectures are illustrated in Figure 3. A detailed examination reveals that VGG16 and Inception V3 achieved a 100% classification rate across all date types and quality grades, showing no misclassifications in the test set. Conversely, the ResNet50 model achieved a slightly lower accuracy of 99.85%. As shown in Figure 3(d), the primary source of confusion for ResNet50 occurred between the **Ajwa** and **Mabroom** varieties. Specifically, a very small percentage of Ajwa samples were misclassified as Mabroom. This minimal error suggests that while these varieties have distinct visual features, the residual learning blocks in ResNet50 may occasionally struggle with fine-grained texture overlaps compared to the deeper 16-layer stack of VGG16 or the multi-scale parallel convolutions of Inception V3.

Table 3: Mean performance results across 5-fold cross-validation

Model	Acc. (Mean $\pm$ Std)	Prec.	Rec.	F1
VGG16	100% $\pm$ 0.00	1.00	1.00	1.00
ResNet50	99.85% $\pm$ 0.05	0.99	0.99	0.99
Inception V3	100% $\pm$ 0.00	1.00	1.00	1.00
CNN [33]	98% (Reported)	NA	NA	NA

6.5 Results and discussions

6.5.1 Experimental results

This subsection presents an in-depth overview of our experimental results using the date dataset, supplemented by a comparative analysis against recent publications that utilized the same dataset. Our experiments involved training three state-of-the-art Transfer Learning (TL) models, with the summarized results displayed in Table 3. The VGG16 and InceptionV3 architectures demonstrated exceptionally high classification performance, both achieving a near-perfect accuracy rate of 100% on the test set. Conversely, the ResNet50 model, while still highly effective, achieved a comparable accuracy rate of 99.85%. These findings not only underscore the effectiveness of the Transfer Learning approach but also provide pertinent insights into the comparative strengths of different CNN architectures in the context of date fruit classification tasks.The detailed confusion matrices and performance metrics (Precision, Recall, F1-Score) for each date category, as generated by the ResNet50, VGG16, and InceptionV3 models, are illustrated in Figure 3.

6.5.2 Results and discussions

The observed near-perfect accuracy ($\geq$ 99.85%) significantly surpasses the 98% baseline of classical CNNs. This validates the hypothesis that Transfer Learning, leveraging weights pre-trained on ImageNet, is superior for agricultural tasks involving limited data. The results suggest that the visual features distinguishing these date varieties are highly separable within the TU-DG dataset. The VGG16 and Inception V3 models both achieved a perfect test accuracy of 100%. VGG16's success can be attributed to its architecture of 16 layers using stacked 3x3 convolutional filters, which are highly effective at capturing fine-grained spatial features in date varieties. Inception V3 achieved similar results by employing parallel convolutions of various sizes (1×1, 3×3, 5×5), allowing it to capture multi-scale features effectively. While ResNet50 slightly underperformed with an accuracy of 99.85%, its use of residual learning and shortcut connections provides superior resilience against the vanishing gradient problem, making it a robust choice for even deeper network implementations.

Transfer Learning acts as a robust foundation for this study for three primary reasons:

- Knowledge Transfer: By leveraging weights pre-trained on the ImageNet dataset (over one million images), the models possess a generalized understanding of visual features that is far superior to training a classical CNN from scratch with limited data.
- Overfitting Resilience: Traditional models trained on small datasets are prone to memorizing noise; how-

	precision	recall	f1-score	support
0	1.00	0.99	1.00	109
1	1.00	0.99	1.00	131
2	0.98	1.00	0.99	99
accuracy			0.99	339
macro avg	0.99	0.99	0.99	339
weighted avg	0.99	0.99	0.99	339

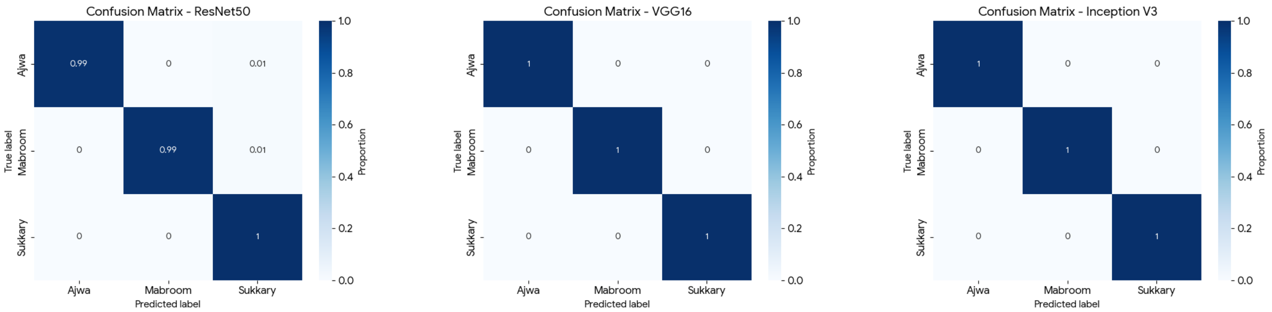
(a) ResNet50

	precision	recall	f1-score	support
0	1.00	1.00	1.00	109
1	1.00	1.00	1.00	131
2	1.00	1.00	1.00	99
accuracy			1.00	339
macro avg	1.00	1.00	1.00	339
weighted avg	1.00	1.00	1.00	339

(b) VGG16

	precision	recall	f1-score	support
0	1.00	1.00	1.00	109
1	1.00	1.00	1.00	131
2	1.00	1.00	1.00	99
accuracy			1.00	339
macro avg	1.00	1.00	1.00	339
weighted avg	1.00	1.00	1.00	339

(c) InceptionV3



(d) ResNet50 (e) VGG16 (f) InceptionV3

Figure 3: Confusion matrices and performance metrics for different models used

ever, the pre-trained weights in TL act as a form of regularization, enabling the model to achieve high performance even in a limited-data context.

– Architectural Depth: TL allows the deployment of deep architectures (e.g., the 48 layers of Inception V3) that would otherwise be impossible to converge effectively using only the 3,383 images in the TU-DG dataset.

6.5.3 Model limitations and challenges

Despite achieving high performance metrics, certain limitations of the TU-DG dataset must be addressed to ensure the reliability of these findings:

– **Dataset Imbalance**: As detailed in Table 2, the Sukkary variety lacks a ”Grade 3” category entirely. This missing data point limits the model’s capacity to recognize low-quality Sukkary dates in real-world environments.

– **Methodological Compensation**: To counter this imbalance, we employed stratified five-fold cross-validation. This ensures that the proportional representation of each available variety and grade is maintained across all training and testing iterations, preventing bias in accuracy reporting.

– **Loss Function Utility**: By utilizing Binary Cross-Entropy (BCE), the system facilitates independent confidence scoring for varieties and quality grades. This approach is more resilient to missing sub-classes than traditional multi-class frameworks, as it does not enforce a rigid probability distribution across non-existent labels.

6.5.4 Practical deployment and real-time evaluation

The near-perfect accuracy achieved on the TU-DG dataset establishes a strong foundation; however, the transition to real-world industrial environments presents unique challenges. In a practical sorting scenario, the model would be integrated into an IoT-enabled conveyor system where high-resolution cameras capture images of date fruits under fluctuating lighting conditions. To bridge the gap between the laboratory and the field, the following considerations are essential:

1. In-Site Testing: While data augmentation simulated variations in brightness and contrast, the models must eventually be tested on uncurated, out-of-distribution images to guarantee that high accuracy persists in harsh agricultural settings.

2. Latency and Hardware: For real-time sorting, model inference time must be minimized. While the pre-trained architectures are deep, deployment on edge devices like NVIDIA Jetson or mobile platforms is necessary to support high-speed processing.

3. Deployment Risks: Large-scale implementation requires addressing technical hurdles, including hardware maintenance in remote rural areas and the mitigation of cybersecurity risks within connected IoT infrastructures.

7 Conclusions and future work

This study evaluated the impact of IoT and deep learning on smart agriculture, with a focus on date classification using transfer learning. Our findings confirm that pre-trained CNNs significantly outperform traditional architectures.

Transfer Learning facilitates faster training, improves generalization, and achieves superior performance with limited datasets. Future research will prioritize the integration of blockchain technology to enhance food traceability and bolster consumer trust. Our findings confirm that pre-trained CNNs significantly outperform traditional architectures for date classification. Transfer Learning facilitates faster training and superior performance with limited datasets. Future research will prioritize testing these models in real-world environments and integrating blockchain technology to enhance food traceability and bolster consumer trust. Building upon the high classification performance established in this study, future research will focus on enhancing the interpretability and deployability of the models:

– **Model Explainability**: We intend to apply explainability techniques such as Grad-CAM to visualize the specific visual features (texture, color, and geometry) that drive the model's grading decisions[cite: 122]. This will ensure that the networks learn relevant agricultural markers rather than dataset-specific noise.

– **Edge Deployment Optimization**: To support real-time sorting in industrial settings, we will investigate lightweight architectures, such as MobileNetV3 with Hard-Swish activation functions, to maintain high accuracy while reducing computational latency for edge device deployment.

– **Addressing Data Imbalance**: Future work will explore the use of Generative Adversarial Networks (GANs) for data augmentation to synthesize samples for underrepresented categories, specifically ”Grade 3” for Sukkary dates.

– **Ensemble Learning and Domain Adaptation**: We aim to implement ensemble learning methods to combine the strengths of VGG16 and Inception V3, alongside domain adaptation techniques to ensure the models generalize effectively across varied agricultural environments and lighting conditions.

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