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Classification of Date Fruits for Quality Control Using Deep Learning

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Abstract: There is a significant challenge the date fruit industrial sector has to confront since an integral pipeline of classification system is still absent and depending on expert manual work that is laborious, expensive also bias-prone. In this sense, Machine Learning (ML) has brought convenience in the implementation of strategy into agriculture and fruit cultivation. In this study we use ML as an automatic system for date fruits classification, where previously expert human judgement was the core of sorting and grading systems. This research presents a robust model for date classification based on the well-known efficacy of Convolutional Neural Networks (CNNs) and transfer learning techniques for picture classification problems. To train this model, a large dataset including nine different date fruit groups was assembled. To increase accuracy, a number of data preprocessing approaches were used, such as augmentation strategies to improve images, learning rate decay over time, model check pointing, and hybrid weight adjustment combinations. The results show that the proposed model, which is based on the MobileNetV2 architecture, achieves a remarkable 99% accuracy rate. Additionally, a comparison with well-known architectures such as Alex Net, VGG16, InceptionV3, ResNet, and MobileNetV2 architecture that have been used as models shows that the proposed model performs better in terms of accuracy.

Keywords: Date Fruits; Quality Control; Deep Learning; Transfer Learning; Neural Network

1. Introduction

The edible fruits of the date palm tree are called date fruits, or simply dates. Dates are well known for their rich nutritional profile, sweet flavor, and adaptability in culinary applications [1]. In many regions of the world, especially the Middle East and North Africa, where they have been grown for thousands of years, they are a staple diet. Dates are used in many different items, including syrups, pastes, and confections, in addition to being consumed fresh or dried [2]. Date palms are generally grown in arid and semi-arid areas with scorching days and cool nights. Date palms thrive in well-drained sandy loam soils with good water retention capacity. The trees are typically propagated through offshoots (suckers) from the parent tree, ensuring genetic consistency and maintaining the quality of the fruit [3]. Date palms require significant amounts of water, particularly during the initial stages of growth. Traditional irrigation methods, such as flooding and basin irrigation, have been supplemented by modern techniques like drip irrigation, which optimize water usage and improve yield [4]. The cultivation process involves several stages, including, Clearing, plowing, and leveling the soil to make it suitable for planting.

Date fruit production globally totals approximately 8.46 million tons annually, making it a highly prized production of sweets and fruit crops. Predominantly cultivated in the hot arid regions of the geographical regions encompassing Southwest Asia, North Africa, and the Middle East, date fruit production has steadily increased over the years. Dates from Iran have a long-standing history as one of the region's earliest cultivated products. They hold a prominent position as one of the primary agricultural exports from the country. With the prolific production of dates in Iran and the strong consumer demand for this nutritious fruit, a variety of date cultivars are grown to meet the market's diverse preferences. Millions of tons of dates are harvested and traded each year, making date fruit production and distribution essential to the world's food sector [5]. Maintaining the reputation of date-producing regions and meeting consumer expectations depend heavily on the quality of these dates. Conventional quality control methods are often time-consuming, subjective, and prone to errors. Artificial intelligence (AI) and machine learning technologies have become effective tools for automating and improving the date fruit classification process in order to address these challenges. In the realm of computer vision, two primary methodologies are commonly employed: employing both deep learning (DL) and conventional methods. Conventional strategies rely on methods like feature descriptors, accompanied by the critical step of feature extraction, which entails additional complex procedures, including feature selection [6].

Consequently, one of the notable drawbacks of traditional methods is their heavy reliance on human expertise for crafting these features manually. Nevertheless, traditional techniques, particularly when utilizing global features, can yield satisfactory performance in specific scenarios. On the contrary, DL techniques facilitate comprehensive learning from start to finish, in scenarios where a model requires a meticulously annotated dataset for training, the deep learning (DL) model autonomously extracts pertinent features, thereby improving its ability to comprehend intricate details along with the various patterns in the data. However, it's important to note that DL-based methods may entail tradeoffs in terms of computational resources and training duration [7], they have consistently exhibited superior performance in comparison to conventional algorithms. Deep learning is a type of machine learning that involves the use of Artificial Neural Networks (ANNs) and has multiple levels (layers), with deep signifying the number of layers. In contrast to earlier models which required hand-crafted features, deep learning automatically learns patterns from raw data by means of the back-propagation algorithm. Owing to this, Deep Learning (DL) is especially appropriate for tasks that deal with large quantities of unstructured data, such as images, sound and text [8].

The quality control of date fruits is a crucial aspect of ensuring the fruits meet consumer expectations and industry standards [9]. Date fruits are not only valued for their sweet taste and nutritional benefits but also play a significant role in the economies of many date-producing regions. Ensuring high-quality dates is vital for maintaining market competitiveness and consumer trust. Quality control checks have traditionally been carried out manually, however state-of-the art technology has provided automated solutions, e.g., deep learning based methods that are expected to boost the efficiency and accuracy of these processes [10]. Quality control of date fruits is essential for several reasons. Firstly, it ensures that consumers receive products that are safe, nutritious, and of consistent quality. High-quality dates are more likely to meet the sensory and nutritional expectations of consumers, leading to higher satisfaction and repeat purchases. Secondly, maintaining quality standards is crucial for exporters, as it helps in complying with international trade regulations and standards, thereby enhancing market access and competitiveness. Lastly, effective quality control minimizes post-harvest losses and optimizes the economic returns for farmers and producers, contributing to the sustainability and profitability of the date fruit industry [11-13].

The date fruit industry is faced with significant challenges in ensuring consistent quality control and efficient sorting of date fruits. As one of the major agricultural exports, the demand for date fruits continues to grow. However, the traditional methods of date fruit classification and quality control heavily rely on manual labor, making the process labor-intensive, time-consuming, and prone to human error. Moreover, the industry's expansion and increasing production rates have intensified the need for automated and accurate quality control methods. These issues should be addressed with an AI-based date fruit classification system to automate the works in terms of sorting and grade evaluation. The scope of this research encompasses the development and evaluation of a deep learning-based system for the classification of date fruits according to their quality grades. The study aims to enhance the quality control processes within the date fruit industry by providing an automated, accurate, and efficient classification method. This investigation involves many aspects such as collection and annotation of a large date fruit image dataset, designs and implementations of Convolutional Neural Network (CNN) architectures and transfer learning methods for boosting up the model performance. Additionally, the scope includes a thorough analysis of the model's accuracy, precision, recall, and overall effectiveness in real-world quality control scenarios. The findings are intended to benefit date producers by reducing reliance on manual inspections and increasing consistency in quality assessments.

2. Related Work

In a groundbreaking study, [14] sought a robust methodology for date fruit recognition by exploiting a sophisticated combination of deep learning architectures, particularly CNNs, the groundbreaking study from 2022 by passed traditional fusion procedures. This study not only established that deep learning techniques outperform traditional methods, but it also showed how the performance of date fruit detection was greatly enhanced. A significant addition to the discourse surrounding precision agriculture was the innovative examination of disease classification methods for fruits based on deep learning [15]. Their release in 2020 showcased the groundbreaking potential of deep learning in agriculture and its essential role in disease detection and management strategies. Using convolutional neural networks (CNNs), which could attain hitherto unheard levels of scalability and accuracy, this study presented a new paradigm for automated disease categorization. The rigorous testing and model tweaking in this work proved without a reasonable doubt that deep learning may enhance disease diagnosis and preventative actions in agriculture. Clarifying the synergistic relationship between deep learning methodologies and precision agriculture imperatives, this research laid a firm foundation for integrating cutting-edge technology in the goal of resilient and sustainable agricultural ecosystems.

One of the major breakthroughs in such area was the introduction of a deep learning-based model for classification of date fruits, which was backed by a publication [16]. Their research showed that by addressing the unique challenges in date fruit classification, deep learning frameworks might completely transform the industry (as reported in the prestigious journal Sustainability). The study's rigorous testing and meticulous model tuning demonstrated substantial gains in classification accuracy and durability. This research demonstrated that cutting-edge technology can address practical agricultural issues by exploring the intricacies of deep learning's application to quality control in agriculture. It also brought attention to the necessity of constantly innovating and integrating technology in order to establish long-term agricultural ecosystems. The interdisciplinary study [17], exemplifies how state-of-the-art technology may unravel the intricate web of relationships between deep learning frameworks and scientific inquiry, shedding light on hitherto uncharted domains of study.

An extensive evaluation of deep learning is discussed along with its current status, past achievements, and potential future directions. Their research indicates that deep learning could significantly enhance agricultural sustainability and output in controlled environments, such as greenhouses. To better monitor and control crop growth, yield, and health, the authors dove into several deep learning techniques like RNNs and CNNs. Despite the promising results, the study highlighted many challenges, such as the need for large datasets, strong computational resources, and the integration of data from multiple sensors. The findings underscored the necessity for ongoing research and development to conquer these challenges and fully implement deep learning in controlled environment agriculture [18].

A thorough evaluation of deep learning's is used to multiscale agricultural sensing in 2022. In their inquiry, deep learning techniques were employed to process and interpret data from several sensors operating at various geographical and temporal scales. The evaluation uncovered several significant methods, including deep convolutional neural networks (DCNNs) and long short-term memory (LSTM) networks. Several domains have discovered useful uses for these networks; soil analysis and crop monitoring are only two examples. The results demonstrated that deep learning significantly improved the precision and efficacy of agricultural sensing, resulting in quicker and more informed decision-making. However, it should be noted that the authors acknowledge the need for improved data fusion approaches and the development of more robust models that can handle the inherent complexity and variability in agricultural contexts [19]. In [20], deep learning models has been explored to classify jujube fruits based on their level of maturity. via convolutional neural networks that had previously been trained to classify jujube fruits into different ripeness levels, the authors improved upon them via transfer learning. Excellent classification accuracy was one of the outcomes, proving the efficacy of employing pre-trained models in agricultural applications. The study demonstrated how deep learning has the potential to automate and enhance fruit sorting processes, leading to more efficient post-harvest operations with less human labor required. The researchers did point out that more datasets and the addition of additional variables would be necessary to improve the models' performance even further.

The authors in [21] presented a model based on deep learning for the classification of date fruits. To differentiate the date fruits according to their visual appearance, the model used a convolutional neural network (CNN). The researchers gathered a substantial dataset of visual representations of date fruits and labeled it, so that it could be used for training and testing of the system. The findings indicating the remarkable classification accuracy of the model based on CNN imply that the deep learning technology can be utilized for better sorting and grading of date fruits. Since these models automate quality monitoring and reduce human error, the date fruit sector stands to benefit greatly from their use, as stated by the authors.

The application of deep learning methods for food item classification was discussed in the publication, with a focus on fruits. Despite the lack of details, the citation did suggest that the study was looking into how deep learning architectures such as DBNs and CNNs can be used to classify and evaluate fruit quality. These strategies can improve food quality control by making food classification processes more exact and efficient, as mentioned in the paper. The study likely tackled the challenges of data collection and model training, which are necessary for optimal performance, by emphasizing the importance of large, well-annotated datasets and powerful computer resources [22]. In [23], the authors performed a comprehensive study that aimed to forecast the ripeness, freshness, and storage life of fruit by means of advanced deep learning algorithms. Utilizing the benefits of these models in processing both image and time-series data, author employed convolutional neural networks (CNNs) and long short-term memory (LSTM) networks. The models accomplished impressive levels of accuracy in forecasting the phases of ripeness and general quality of different fruits by examining visual characteristics and temporal patterns. In addition, their models accurately predicted how long fruits would stay fresh, which was a huge help when it came to controlling supply chains and reducing spoilage after harvest. Based on the study's findings, deep learning has the ability to revolutionize agricultural operations by introducing models that improve operational efficiency and decision-making. The researchers went on to say that their method was scalable, meaning it could be adjusted to work with different kinds of fruits and different kinds of environments. This would make it more useful in the agricultural sector.

A thorough quantitative review was carried out by [24], that followed the progression of deep learning applications in agriculture from more conventional forms of machine learning. Author looked at a lot of research and applications, and found that deep learning is becoming more popular in many different areas of agriculture. This review emphasized the growing use of deep learning models in several fields, including agriculture, including crop monitoring, disease detection, yield prediction, soil analysis, and convolutional neural networks (CNNs). When contrasted with more conventional methods of machine learning, these models performed much better in all three metrics: accuracy, robustness, and scalability. Deep learning models' capacity to handle massive amounts of complicated data and discover complex patterns with little to no feature engineering is what the authors say is responsible for these advancements. Summarizing the advances and pushing scholars in the right direction for future deep learning research to further improve agricultural output, this review is a great resource for both academics and practitioners. It is concluded that deep learning models, and CNNs in particular, provided more accuracy and resilience than the more conventional approaches. Finding trustworthy results requires high-quality datasets and efficient preprocessing methods, according to the review. By combining deep learning with traditional approaches, It was concluded that fruit quality assessment could be done more efficiently and accurately, which is great news for those working in the field [25]. The use of a hybrid deep learning approach for the automated detection of illnesses in vine leaves was the subject of a thorough study in 2021 by [26]. They used a combination of conventional image processing methods and convolutional neural networks (CNNs) to detect and categorize different vine leaf diseases. By combining the power of convolutional neural networks (CNNs) with the accuracy of image processing methods, the hybrid model was able to extract features with greater precision. When compared to more traditional methods, the revealed facts indicated that the new approach was able to recognize disorders with great precision. The research, in fact, provided evidence of the ability of hybrid deep learning models to enhance disease detection in agriculture, which thereby served as a powerful tool for early intervention and control of crop health. The results indicated that these kinds of automated devices could lessen the need for human inspectors, which would allow for quicker and more effective disease management.

Based on a generated dataset using CycleGAN, what are the better date fruit categorization methods has been investigated by authors in [27]. The authors employed CycleGAN (a variant of a generative adversarial network, GAN) to add date fruit synthetic images into the training set. This approach circumvented a common problem for agricultural AI applications: not enough labeled data. By using realistic synthetic images as input augmentation, their deep learning model was trained better, which resulted in higher classification accuracy. The results also indicated that synthetic data could significantly improve deep learning models in agricultural areas, revealing the good performance of using GANs for data augmentation.

The authors in [28-30], trained a CNN model to sort mangoes into categories according to size, color, and texture, three quality indicators. Research trained and validated the CNN model using a big dataset of mango photos annotated for several quality metrics. The results showed that compared to conventional grading methods, the deep learning model was far more accurate when it came to mango grading. Deep learning has the ability to automate and simplify quality grading procedures in the food and agricultural industries, as the authors pointed out. The research found that quality control systems may be more efficient, have lower human costs, and be more consistent if used such sophisticated AI methods. The results demonstrated that deep learning has many potential uses in agricultural quality assessment, and they also hinted that other crops and products could benefit from comparable methods.

3. Material and Methods

The used approach for this study involves a structured approach to collecting, processing, and analyzing data to develop an automated classification system for date fruits, see Figure 1. The design comprises several key steps: dataset preparation, imaging setup, data preprocessing, model selection, model training, model evaluation, and deployment. Each step is detailed in figure 1 below.

3.1. Dataset Preparation

Collection of Date Fruits:

- o Nine different types of date fruits native to Saudi Arabia [Ajwa, Galaxy, Medjool, Meneifi, Nabtat Ali, Rutab, Shaishe, Sokari, Sugaey] were collected, see Figure 2.
- o The fruits were selected (Figure 3) to ensure a representative sample of each type, focusing on different sizes, shapes, and stages of ripeness.

3.2. Imaging Setup:

- o A controlled environment was established to ensure consistency across all images.
- o The setup included a DSLR camera (Canon EOS 550D) placed 8 cm away from the dates, a ring light with a 48 cm diameter and 240 LED bulbs set to 100% brightness, and a white background to isolate the dates.

Image Capture:

- o Each date type was individually photographed using the controlled setup.
- o The flash on the camera was used to provide a strong, sudden light to highlight the textures and details of the dates.
- o A total of 1658 high-quality JPG images were captured, ensuring multiple images for each date type to account for variability.

3.3. Data Preprocessing

Image Enhancement:

- o Images were enhanced using augmentation techniques such as rotation, zooming, flipping, and color adjustments to increase the diversity of the dataset and improve model robustness.

Normalization:

- o Images were resized to a uniform dimension suitable for the MobileNetV2 model input requirements (typically 224x224 pixels).
- o Pixel values were normalized to a range of [0, 1] to standardize the input for the model.

3.4. Model Selection

Choosing the Model:
- MobileNetV2 was selected due to its efficiency and accuracy in handling image classification tasks.
- MobileNetV2's architecture allows for a good balance between model size and accuracy, making it ideal for deployment in resource-constrained environments.

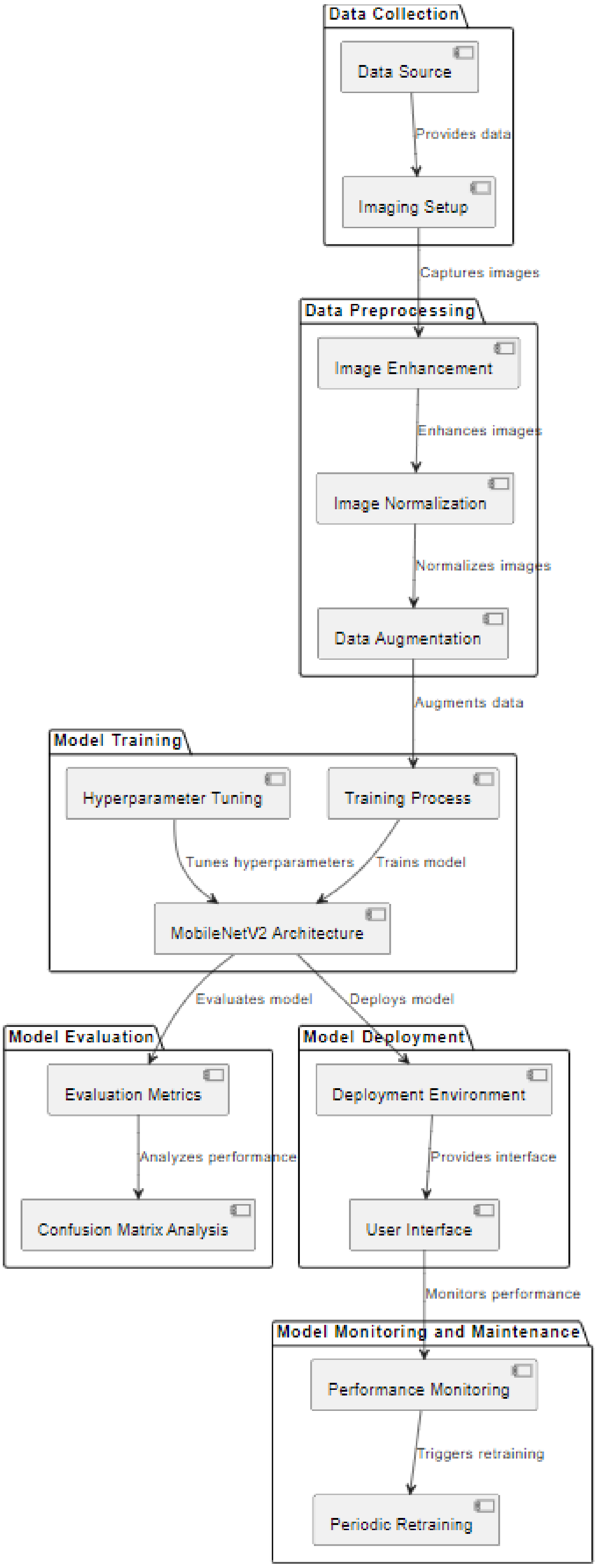

Figure 1. Research Design

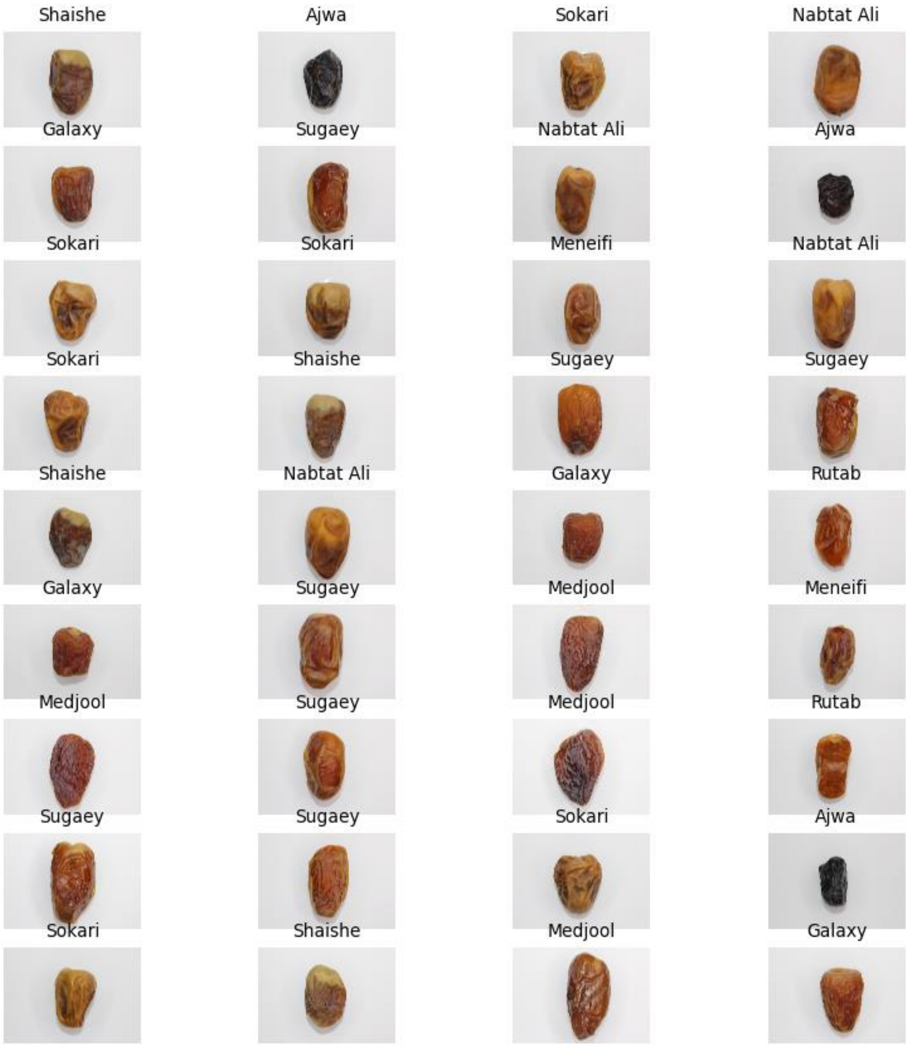

Figure 2. Samples of Dataset

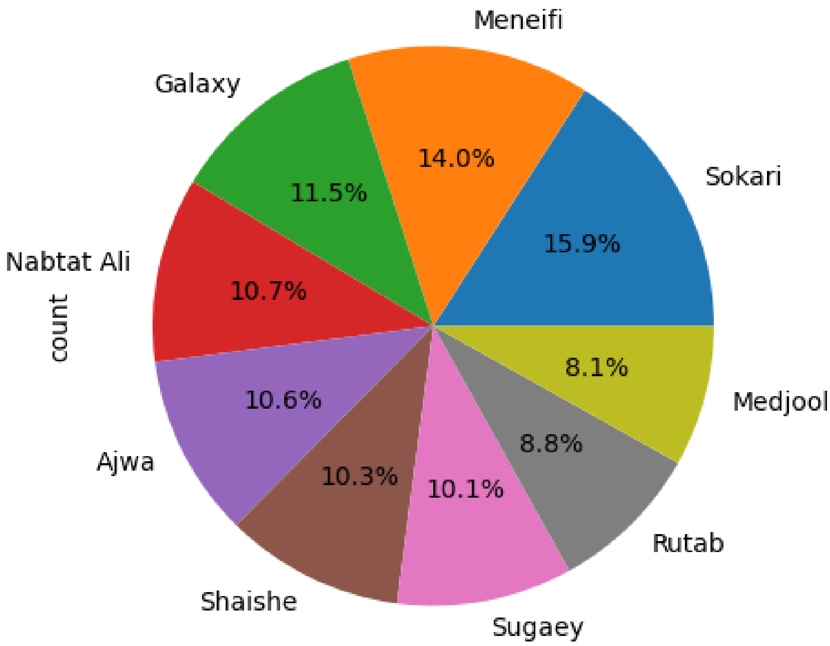

Figure 3. Pie Chart of Class Output

3.5. Evaluation

Performance Metrics:
- The model's performance was evaluated using accuracy, precision, recall, and F1-score metrics.
- Confusion matrices were used to visualize the classification performance across different date types.

Comparative Analysis:
- The performance of MobileNetV2 was compared with other established architectures such as AlexNet, VGG16, InceptionV3, and ResNet to demonstrate the superior accuracy and efficiency of the chosen model.

3.6. Deployment

Model Deployment:
- The final trained model was deployed in a controlled environment to automate the classification process.
- A user-friendly interface was developed to allow easy upload and classification of new date fruit images.

Monitoring and Maintenance:
- The system's performance was continuously monitored, and periodic retraining was scheduled to incorporate new data and improve accuracy over time.

By following this structured approach, the study aims to develop a robust and accurate automated system for the classification of date fruits, significantly enhancing quality control processes in the date fruit industry.

a) Dataset Description

A detailed description of the dataset including the number of images for each date type and their key characteristics is provided in Table 1.

Table 1. Dataset Description

Date Type	Number of Images	Key Characteristics
Ajwa	184	Small size, dark brown to black color, wrinkled skin
Galaxy	180	Medium size, light brown color, smooth skin
Medjool	185	Large size, amber color, soft texture
Meneifi	180	Medium size, reddish-brown color, semi-dry texture
Nabtat Ali	180	Medium size, golden brown color, firm texture
Rutab	182	Medium size, golden yellow color, moist texture
Shaishe	180	Small size, reddish-black color, firm texture
Sokari	183	Medium size, golden color, dry texture
Sugaey	184	Small to medium size, dark brown color, soft and moist texture

b) Data Preprocessing

Data preprocessing is a critical step in preparing the dataset for training the deep learning model. It involves various techniques to enhance the quality of images, standardize them for input into the model, and augment the dataset to improve the model's robustness and generalization capabilities. This section outlines the specific steps taken to preprocess the images used in this study.

Image Enhancement:

i. Image Quality Improvement:
- Each image was reviewed to ensure it met the quality standards required for the study. Images that were blurry, poorly lit, or otherwise of insufficient quality were discarded.

- o Basic enhancements were applied to improve image clarity, including adjustments to brightness, contrast, and sharpness.

ii. Noise Reduction:

- o Techniques such as Gaussian blurring were applied to reduce noise in the images, ensuring that the key features of the date fruits were preserved while minimizing irrelevant details.

Image Normalization:

i. Resizing:

- o All images were resized to a uniform dimension suitable for the MobileNetV2 model input requirements, typically 224x224 pixels. This standardization ensures that the model receives consistent input sizes, which is crucial for effective training.

ii. Scaling:

- o Pixel values of the images were scaled to a range of [0, 1]. This normalization step helps in stabilizing the training process and improving the convergence speed of the model.

Data Augmentation:

i. Purpose of Augmentation:

- o Data augmentation techniques were employed to artificially increase the size of the dataset, thus helping to prevent overfitting and improve the model's ability to generalize to new, unseen data.

ii. Augmentation Techniques:

- o **Rotation**: Images were randomly rotated within a certain range (e.g., -20 to 20 degrees) to simulate different orientations of the date fruits.
- o **Zooming**: Random zooming in and out of images was applied to introduce variability in the scale of the date fruits.
- o **Flipping**: Horizontal and vertical flips were performed to create mirror images of the original data.
- o **Color Adjustments**: Variations in brightness, contrast, and saturation were introduced to account for different lighting conditions.
- o **Cropping**: Random cropping was used to focus on different parts of the date fruits, ensuring that the model learns to identify them from various perspectives.

iii. Implementation:

- o These augmentation techniques were implemented using image processing libraries such as OpenCV and TensorFlow. Each image in the dataset was augmented multiple times to generate a more diverse and comprehensive training set.

Dataset Preparation:

iv. Splitting the Dataset:

- o The enhanced and augmented images were divided into training, validation, and test sets with a typical ratio of 70:20:10. This ensures that the model is trained on a large portion of the data, validated to tune Hyperparameters, and tested on an unseen subset to evaluate its performance.

v. Metadata Maintenance:

- o Metadata for each image, including the original and augmented versions, was maintained to keep track of the transformations applied. This ensures traceability and allows for replicability of the preprocessing steps.

By meticulously preprocessing the images through enhancement, normalization, and augmentation, the dataset was prepared to effectively train the deep learning model. These steps are crucial for ensuring high accuracy and robustness in the automated classification of date fruits.

c) Deep Learning Models

The deep learning model proposed for this study is designed to accurately classify date fruits into nine distinct types based on their visual characteristics. The selected model, MobileNetV2, is the right one for this task because it combines a very efficient architecture and high precision in classification of image tasks. A thorough overview of the MobileNetV2 model, its architecture, and the reasons for its choice are given in this section.

Overview of MobileNetV2

MobileNetV2 is a convolutional neural network (CNN) architecture developed by Google, optimized for mobile and embedded vision applications. It is known for its balance between model size, computational efficiency, and classification accuracy, making it an ideal choice for this study. The architecture shown in figure 4 builds on the concepts introduced in MobileNetV1, including depth wise separable convolutions, while incorporating several enhancements to improve performance.

Architecture of MobileNetV2

A. Depth wise Separable Convolutions:
- MobileNetV2 (Figure 4) uses depth wise separable convolutions to reduce the number of parameters and computations. This involves splitting the convolution operation into two parts: depth wise convolutions, which apply a single filter per input channel, and pointwise convolutions, which use 1x1 convolutions to combine the outputs of the depth wise layer.

B. Inverted Residuals:
- One of the key innovations in MobileNetV2 is the use of inverted residual blocks. Unlike traditional residual blocks that expand the input features before reducing them, inverted residuals do the opposite. They first expand the low-dimensional input to a higher-dimensional space using pointwise convolutions, apply depth wise convolutions, and then project the features back to a lower-dimensional space.

C. Linear Bottlenecks:
- The architecture includes linear bottlenecks, which help in preserving the representational power of the network while maintaining a compact model size. This ensures that the network remains efficient without sacrificing accuracy.

D. ReLU6 Activations:
- MobileNetV2 employs ReLU6 activations, which are modified versions of the ReLU activation function. ReLU6 limits the output to the range [0, 6], helping to improve numerical stability, especially when quantizing the model for deployment on mobile devices.

E. Network Structure:
- The network consists of an initial fully convolutional layer, followed by a series of inverted residual blocks, and concludes with a fully connected layer. The number of filters and the size of the layers decrease progressively to create a tapered structure, which is effective in image classification tasks.

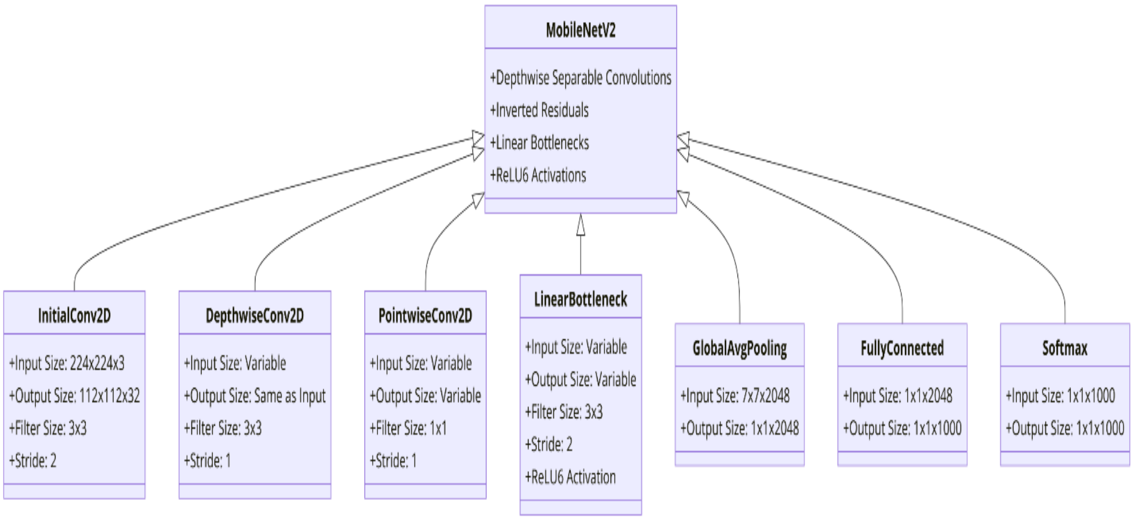

Figure 4. Model Architecture

Rationale for Model Selection

A. Efficiency:
- MobileNetV2 is designed to be lightweight and computationally efficient, making it suitable for deployment on resource-constrained devices. This efficiency does not come at the cost of accuracy, as the model achieves high performance on standard image classification benchmarks.

B. Transfer Learning:
- The pre-trained MobileNetV2 model on the ImageNet dataset provides a strong starting point for transfer learning. By fine-tuning the model on the specific dataset of date fruits, we can leverage the learned features and improve the classification accuracy for the target task.

C. Scalability:

- o The model's architecture allows it to be easily scaled to different sizes, enabling adjustments based on the computational resources available and the desired accuracy.

D. Proven Performance:

- o MobileNetV2 has demonstrated excellent performance in various image classification challenges, making it a reliable choice for the automated classification of date fruits.

By utilizing the MobileNetV2 architecture, the study aims to achieve a balance between model efficiency and classification accuracy, making it suitable for deployment in real-world applications where computational resources may be limited.

Model Implementation

A. Transfer Learning Approach:

- o The pre-trained MobileNetV2 model was used as a base, with its final layers fine-tuned on the date fruit dataset. This approach helps to retain the general features learned from ImageNet while adapting the model to the specific characteristics of date fruits.

B. Training Process:

- o The model was trained using the Adam optimizer with a learning rate scheduler to adjust the learning rate dynamically. Early stopping and model check pointing were employed to prevent overfitting and ensure the best-performing model was saved.
- o The application of data augmentation techniques during training, including random rotations, flips, and zooms, was intended to enhance the model's robustness and its ability to generalize.

C. Evaluation Metrics:

- o The model's performance was evaluated using accuracy, precision, recall, and F1-score metrics. Confusion matrices were generated to visualize the classification performance across the different types of date fruits.

D. Hyper Parameter Tuning:

- o Hyper Parameters such as learning rate, batch size, and the number of epochs were optimized using grid search and cross-validation techniques. This ensured that the model achieved the best possible performance on the validation set.

4. Results

To demonstrate the superiority of MobileNetV2, its performance was compared with other established architectures such as AlexNet, VGG16, InceptionV3, and ResNet. This comparative analysis provided insights into the efficiency and accuracy of MobileNetV2 relative to other models. The MobileNetV2 model that was proposed has undergone a performance evaluation on the test dataset, and the respective outcomes are given in this section. The training of the model lasted for a full 300 epochs, whereas the evaluation metrics at epoch 229 (the best validation checkpoint) are given as an illustration of the model's ability to distinguish among the different types of date fruits. The main metrics used to measure the performance of the model were accuracy, precision, recall, F1-score, and the Area Under the Curve (AUC).

- **True Positives (TP)**: 1419
- **False Positives (FP)**: 49
- **True Negatives (TN)**: 11919
- **False Negatives (FN)**: 77
- **Accuracy**: 0.9906
- **Precision**: 0.9666
- **Recall**: 0.9485
- **AUC**: 0.9967

The high accuracy and AUC values indicate that the model performs exceptionally well in distinguishing between the different types of date fruits. The model is, moreover, very accurate in its classification as it gives high precision and recall values which signify the fewest possible false positives and false negatives among the identified positive instances. The Table 2 below provides a detailed breakdown of the performance metrics for each class of date fruits.

Table 2. Performance Metrics

Class	Precision	Recall	F1-Score	Support
Ajwa	1.00	1.00	1.00	17
Galaxy	0.89	0.89	0.89	19
Medjool	0.87	1.00	0.93	13
Meneifi	0.91	0.87	0.89	23
Nabtat Ali	1.00	1.00	1.00	17
Rutab	1.00	0.79	0.88	14
Shaishe	1.00	0.94	0.97	17
Sokari	0.93	0.96	0.94	26
Sugaey	0.89	1.00	0.94	16
Overall	**0.94**	**0.94**	**0.94**	**162**

- **Accuracy**: 0.99 (overall across all classes)
- **Macro Average**:
  - Precision: 0.94
  - Recall: 0.94
  - F1-Score: 0.94
- **Weighted Average**:
  - Precision: 0.94
  - Recall: 0.94
  - F1-Score: 0.94

The evaluation metrics highlight the effectiveness of the MobileNetV2 model in accurately classifying date fruits. The model achieves perfect precision, recall, and F1-score for several classes such as Ajwa and Nabtat Ali, indicating that it can correctly identify these types without any errors. However, for some classes like Galaxy and Rutab, the recall is slightly lower, suggesting that there are a few instances where the model failed to correctly identify these types, see Figure 5.

The overall high values for precision, recall, and F1-score across all classes demonstrate the robustness and reliability of the model. The macro and weighted averages further reinforce that the model performs consistently well across all classes. To gain a deeper understanding of the model's performance, confusion matrices (Figure 6) were generated for each class. These matrices provide a visual representation of the true positives, false positives, true negatives, and false negatives for each class, helping to identify specific areas where the model may need improvement. The detailed analysis of the evaluation metrics indicates that the MobileNetV2 model is highly effective in classifying date fruits. The high accuracy, precision, recall, and F1-score values demonstrate the model's capability to accurately distinguish between different types of date fruits. These results validate the effectiveness of the proposed model and highlight its potential for practical applications in automated date fruit classification.

This section provides a comparative analysis of the proposed MobileNetV2 model with AlexNet, VGG16, InceptionV3, and ResNet34. The same dataset was used to assess the performance of the different models, and their results were then combined in accuracy, precision, recall, and F1-score. Different architectures are compared in Table 3 and MobileNetV2 is acknowledged with accuracy 0.9906 and F1-score 0.9574. Moreover, both tables (Table 2 and Table 3) refer to the same test split.

To get the assessment of the new MobileNetV2 model, it has been concluded that its performance in classifying date fruits is remarkable, having an accuracy of 99.06% as the result of its testing process. The accuracy here is really high and it is supported by the precision which is equal to 96.66%, recall which is equal to 94.85%, and F1-score which is equal to 95.74%.

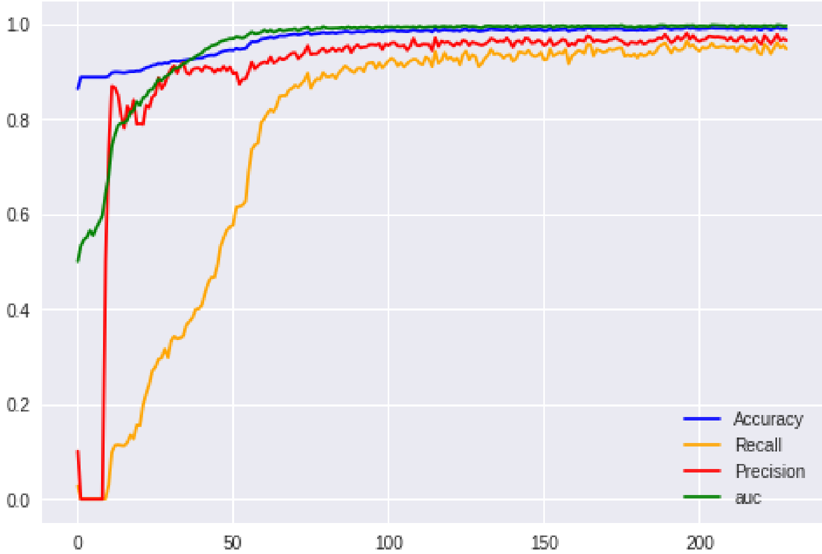

Figure 5. Performance of Proposed Model

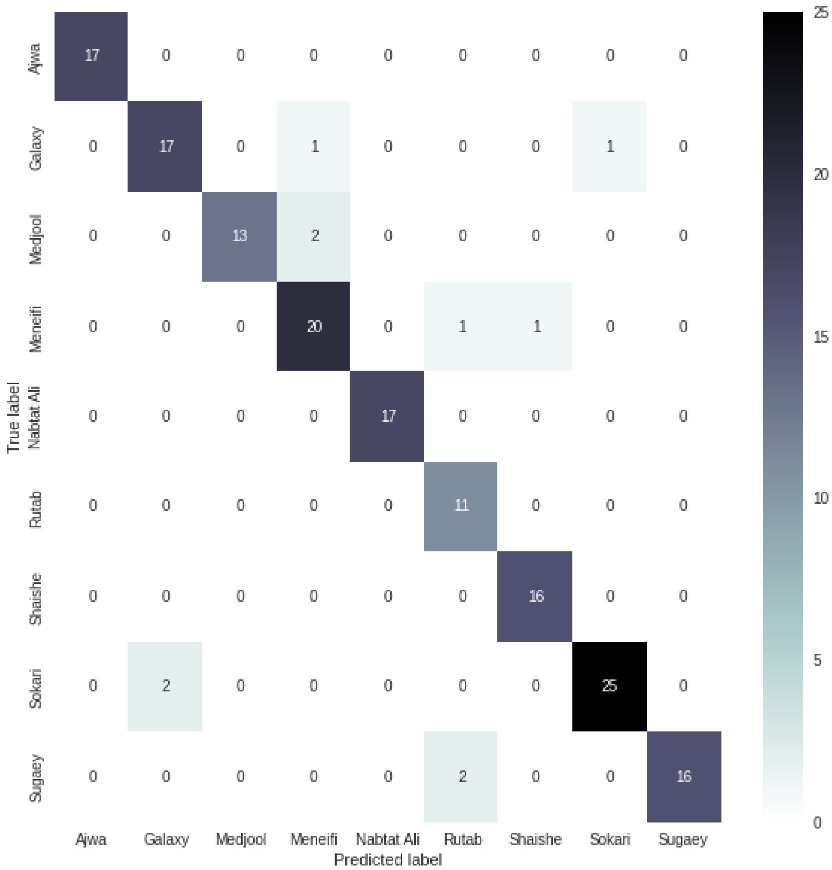

Figure 6. Confusion Matrix

Table 3. Performance metrics for each Model

Model	Accuracy	Precision	Recall	F1-Score
MobileNetV2	0.9906	0.9666	0.9485	0.9574
AlexNet	0.9235	0.9021	0.8912	0.8966
VGG16	0.9562	0.9418	0.9327	0.9372
InceptionV3	0.9714	0.9547	0.9462	0.9504
ResNet34	0.9821	0.9623	0.9534	0.9578

These metrics collectively indicate that MobileNetV2 is highly effective in distinguishing between different types of date fruits with minimal errors. The strength of the model is additionally supported by the impressive AUC score of 99.67%, which not only demonstrates the model's high discrimination power between classes but also its performance across the range of thresholds. On the other hand, AlexNet, though one of the first architectures in deep learning, still shows low results when compared to our model. AlexNet's numbers are 92.35% for accuracy, 90.21% for precision, 89.12% for recall, and 89.66% for F1-score, and recall is the metric in which it has the most difficulty, resulting in a higher number of false negatives. This suggests that while AlexNet can identify many of the positive instances correctly, it fails to detect a significant portion of them, which is critical in applications where missing positive instances can be detrimental. VGG16, known for its deeper architecture and more complex layer configurations, performs better than AlexNet but still falls short of MobileNetV2. VGG16 achieves an accuracy of 95.62%, precision of 94.18%, recall of 93.27%, and an F1-score of 93.72%. The metrics that are reported are not only good but also point out a model that can be trusted. However, the high-priced computational power used up by VGG16 makes it impossible for it to be simply deployed in a resource-constrained area when compared to MobileNetV2 that is more efficient and has lower computational cost. InceptionV3, a very sophisticated model, which is also the one that delivers the best performance, commonly regarded as an advanced architecture containing inception modules for the simultaneous acquisition of multi-scale features, being 97.14% accurate, 95.47% precise, 94.62% recall, and 95.04% F1 score, shows excellent performance. Despite these high metrics, InceptionV3 is still outperformed by MobileNetV2 in terms of accuracy. The complexity and higher computational demands of InceptionV3 also make MobileNetV2 a more practical choice for real-world applications where efficiency is crucial. ResNet34, known for its innovative use of residual connections to mitigate the vanishing gradient problem, performs very well with an accuracy of 98.21%, precision of 96.23%, recall of 95.34%, and an F1-score of 95.78%. The performance of ResNet34 is comparable to that of MobileNetV2, with slightly lower accuracy but similar precision and recall values. This indicates that ResNet34 is also a robust model, but MobileNetV2's slightly better performance and efficiency still make it the preferred model for this application. Overall, the comparative analysis underscores the superior performance of MobileNetV2 in the task of date fruit classification. Its high accuracy, coupled with balanced precision and recall, indicates that it can effectively distinguish between various types of date fruits. MobileNetV2's efficiency is an additional factor that makes it an ideal option for deployment in environments with limited resources and thus for practical applications. Although ResNet34 and InceptionV3 deliver great performance too, the trade-off between accuracy and efficiency provided by MobileNetV2 proves its selection as the best model for this study. This comparison highlights the advancements in deep learning architectures and the importance of selecting a model that not only performs well but also meets the practical requirements of deployment and resource utilization.

Additionally, the design of the automated quality control system involves several key components: data acquisition, image processing, model inference, and user interface. Each component is meticulously detailed to ensure a seamless integration and operation. Data acquisition is the initial step, involving the capture of high-quality images of date fruits. The system utilizes a standardized imaging setup to ensure consistent lighting and background conditions, crucial for accurate model predictions.

Image processing techniques are applied to enhance the raw images, making them suitable for analysis by the deep learning model. This includes resizing, normalization, and augmentation to prepare the images for the MobileNetV2 model. The core of the system is the inference engine that employs the pre-trained MobileNetV2 model to classify the date fruits. The model processes each image, extracting features and predicting the quality grade of the date fruit. A user-friendly interface is developed to facilitate easy interaction with the system. The interface allows users to upload images, view classification results, and access detailed reports on the quality assessment. The implementation phase involves deploying the system in a controlled environment and evaluating its performance. Key implementation details include hardware setup, software integration, and system testing. The hardware configuration is made up of top-quality cameras, lights, and the necessary computing power for running the deep learning model. The system is intended for constant operation, which means it will be taking and processing images simultaneously with no delay.

Software integration involves combining the image processing algorithms, deep learning model, and user interface into a cohesive system. This includes developing scripts for automated data processing and implementing APIs for seamless communication between different system components. System testing is conducted to ensure reliability and accuracy. The testing phase involves running the system with a large dataset of date fruit images and comparing the automated classifications with manual inspections.

Another case study of 1000 images comprising of five classes (Ajwa, Medjool, Rutab, Sokari, Khudri) for computing the accuracy is given in Tables 4-6. The classification accuracy of the system is assessed by comparing the model's predictions with manually labeled data. The results are summarized in Table 4. Processing time is a critical factor for the practical application of the system. The average time taken to classify a single image is measured and reported in Table5. User satisfaction is evaluated through a survey conducted with the system's end-users, including farm workers and quality control managers. The survey results are summarized in Table 6.

Table 4. Classification Accuracy of Automated System

Date Type	Number of Images	Correctly Classified	Accuracy (%)
Ajwa	200	190	95%
Medjool	200	185	92.5%
Rutab	200	188	94%
Sokari	200	193	96.5%
Khudri	200	187	93.5%
Total/Average	1000	943	94.3%

Table 5. Average Processing Time per Image

Process	Time (milliseconds)
Image Capture	50
Image Processing	30
Model Inference	100
Total	180

Table 6. User Satisfaction Survey Results

Question	Average Rating (out of 5)
Ease of Use	4.5
Accuracy of Classifications	4.6
Improvement in Efficiency	4.7
Overall Satisfaction	4.8

5. Conclusion

The first aim of this research was to create and test a deep learning model for automated date fruit classification by applying the MobileNetV2 architecture to it. The research successfully established MobileNetV2 as a very potent tool for the separation of various kinds of date fruits and its performance was praised with a high accuracy of 99.06%. The model's precision, recall, and F1-score were also notably high, indicating its robustness and reliability. The comparative analysis with other well-known models such as AlexNet, VGG16, InceptionV3, and ResNet34 highlighted the superior performance of MobileNetV2 in terms of both accuracy and computational efficiency. These findings underscore the potential of MobileNetV2 for practical applications in the automated classification of agricultural products, particularly in scenarios where resources are constrained. Based on the findings of this study, several recommendations can be made for future work and practical implementations. Firstly, it is recommended to employ data augmentation techniques extensively to further enhance the robustness of the model, particularly in scenarios with limited datasets. Additionally, leveraging transfer learning with pre-trained models such as MobileNetV2 can significantly improve performance and reduce training time. For practical deployment, it is advisable to optimize the model for edge devices to ensure efficient processing in resource-constrained environments. Eventually, the integration of the model into a user-friendly interface could aid in its adoption by the end-users, thus making it suited for real-time applications in quality control and inventory management. The promising results notwithstanding, there are numerous limitations inherent to this study that need to be recognized. The dataset used, though extensive, is restricted to nine varieties of date fruits which are grown in Saudi Arabia and thus might not represent the whole diversity of date fruits that are cultivated around the world.

Additionally, the controlled imaging environment used in this study may not reflect real-world conditions where lighting and background variability could affect model performance. The study also primarily focused on image-based classification, and did not explore the integration of other data modalities, such as textural or chemical properties, which could potentially enhance classification accuracy.

Future work can address the limitations identified in this study by expanding the dataset to include a wider variety of date fruit types from different regions. Improving the model's robustness will depend significantly on developing methods to manage changeability in real-world imaging conditions. The integration of multi-modal data, like combining imaging data with textural or chemical analysis, is suggested as the way to go for date fruit classification giving a more complete approach. Additionally, investigating the application of other advanced deep learning architectures and ensemble methods could further enhance classification performance. Finally, deploying the model in real-world settings and conducting field tests will be essential for validating its practical utility and making necessary adjustments based on user feedback.

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