## DATE FRUIT CLASSIFICATION USING ROBOTIC HARVESTING IN NATURAL ENVIRONMENT IN PYTHON

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#### ABSTRACT

An accurate vision system to classify and analyze fruits in real time is critical for harvesting robots to be cost-effective and efficient. However, practical success in this area is still limited, and to the best of our knowledge, there is no research in the area of machine vision for date fruits in an orchard environment. In this work, we propose an efficient machine vision framework for date fruit harvesting robots. The framework consists of three classification models used to classify date fruit images in real time according to their type, maturity, and harvesting decision. In the classification models, deep convolutional neural networks are utilized with transfer learning and fine-tuningon pretrained models. To build a robust vision system, we create a rich image datasetof date fruit bunches in an orchard that consists of more than 8000 images of five datetypes in different pre-maturity and maturity stages. The dataset has a large degree of variations that reflects the challenges in the date orchard environment including variations in angles, scales, illumination conditions, and date bunches covered by bags. The proposed date fruit classification models achieve accuracies of 99.01%, 97.25%, and 98.59% with classification times of 20.6, 20.7, and 35.9 msec for the type, maturity, and harvesting decision classification tasks, respectively.

#### **1.INTRODUCTION**

In this work, we propose an efficient machine vision framework for date fruit harvesting robots. The framework consists of three classification models used to classify date fruit images in real time according to their type, maturity, and harvesting decision. In the classification models, deep convolutional neural networks are utilized with transfer learning and fine-tuning on pre-trained models. To build a robust vision system, we create a rich image dataset of date fruit bunches in an orchard that consists of more than 8000 images of five date types in different pre-maturity and maturity stages. However, manual harvesting is dangerous and highly labor-intensive as well as inefficient in terms of both time and the economy. Such methods are the major cause of delaysin the date production cycle and account for more than 45% of the date production cost. we create a rich image dataset of date fruit bunches in an orchard that consists of more than 8000 images. The dataset has a large degree of variations that reflects the challenges in the date orchard environment including variations in angles, scales, illumination conditions, and date bunches covered by bags. The proposed date fruit classification models achieve accuracies of 99.01%, 97.25%, and 98.59%.

## **3.LITERATURE SURVEY**

Date fruit classification using robotic harvesting would involve gathering and analyzing research articles, conference papers, and other scholarly sources related to the topic. Here's a structured approach to conducting such a survey:

- \*Define Search Keywords\*: Identify relevant keywords related to "date fruit classification," "robotic harvesting," and any specific techniques or technologies involved (e.g., machine learning, computer vision, robotics).
- 2. \*Search Academic Databases\*: Utilize academic databases such as PubMed, IEEE Xplore, Google Scholar, and ScienceDirect to search for articles. Use the identified keywords to narrowdown the search results.
- 3. \*Review Relevant Papers\*: Read abstracts and summaries of the papers to determine their relevance. Look for studies that specifically address date fruit classification using robotic harvesting techniques.
- 4. \*Filtering\*: Filter out papers that are not directly related to the topic or do not provide substantial insights into the methodologies or findings.
- 5. \*Analyze Methodologies\*: Examine the methodologies employed in the selected papers. Pay attention to the types of sensors, algorithms, and robotic systems utilized for date fruit classification and harvesting.
- 6. \*Compare Results\*: Compare the results obtained by different studies in terms of classification accuracy, harvesting efficiency, and any other relevant metrics.
  - 7. \*Identify Gaps and Challenges\*: Identify any gaps or challenges in the existing literature. This could include limitations in the current approaches, areas for improvement, or unresolved research questions.
  - 8. \*Summarize Findings\*: Summarize the key findings from the literature survey, including the methodologies used, challenges faced, and potential avenues for future research.
  - 9. \*Critically Evaluate\*: Critically evaluate the strengths and weaknesses of the existing approaches and propose recommendations for future research directions.
  - 10. \*Cite Sources\*: Ensure proper citation of all the sources used in the literature survey.

#### **3.PROBLEM STATEMENT**

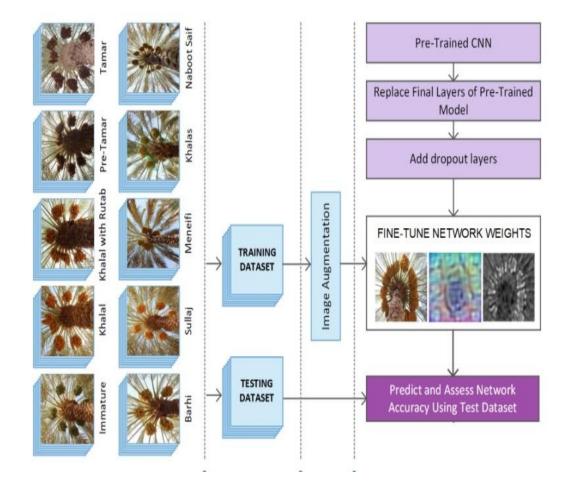
Date palm cultivation is a labor-intensive process, particularly during the harvesting phase, which involves the classification of ripe and unripe fruits for efficient collection. Traditional methods rely heavily on manual labor, leading to high labor costs, inconsistent harvesting quality, and increased susceptibility to human error. As demand for dates continues to rise globally, there is an urgent need for automated solutions to streamline the harvesting process.One of the critical challenges in automated date fruit harvesting is the accurate classification of ripe and unripe fruits in real-time. Existing classification methods often lack the precision required to differentiate between fruits at various stages of ripeness, leading to inefficiencies and yield losses. Additionally, the implementation of robotic harvesting systemsintroduces complexities related to the integration of sensors, algorithms, and robotic manipulators to perform delicate harvesting tasks effectively.Therefore, the primary problem addressed in this research is the development of a robust automated system capable of accurately classifying date fruits based on their ripeness using advanced sensing technologies and machine learning algorithms. This system should seamlessly integrate with robotic harvesting platforms to enable efficient and precise harvesting while minimizing damage to the fruits and maximizing overall yield.

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#### **4.PROPOSED SYSTEM**

In this paper author is describing concept to classify date fruit by modifying pre classifier such as 'VGG16 and Alexnet', VGG16 and Alexnet are the already developed model by using images from imagenet and we can customised this pre classifier with our own images by using concept called Transfer Learning. While using Transfer Learning we can make pre classifier to forget its last prediction layer

#### **5.SYSTEM ARCHITECTURE**



#### **MODULES**

- Upload date Fruit Dataset:
- Fine Tune & Transfer Learning with VGG16:
- Fine Tune & Transfer Learning with Alexnet:
- Date Fruit Classification with 3 Classifiers:
- VGG16 and Alexnet Accuracy Graph

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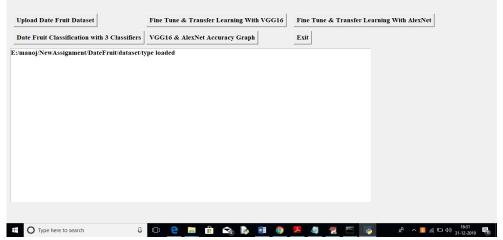
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Date Fruit Classification for Robotic Harvesting in a Natural Environment Using Deep Learning



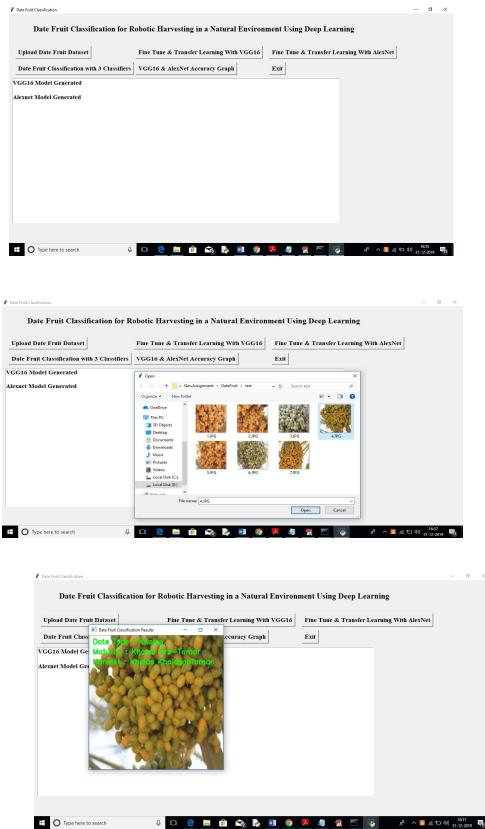
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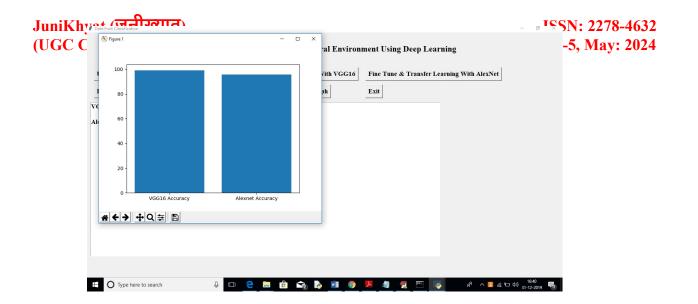
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## 8.CONCLUSION

A real-time machine vision framework for date fruit harvesting robots in an orchard environment was proposed based on deep learning. The framework consisted of three models used to classify date fruit bunches according to their type, maturity, and harvesting decision. Transfer learning with fine-tuning was used in the classification tasks. Two pre-trained CNN models were investigated, namely AlexNet and VGG-16. To build a robust machine vision system, we used a rich image dataset of five date types for all maturity stages. The dataset was designed with a large degree of variation that represents the challenges in naturalenvironments and date fruit orchards. The proposed approach achieved excellent classification accuracies on this challenging dataset with a high classification rate. The results showed that a pre-trained CNN could achieve robust date fruit classification without the pre- processing of images to remove background noise or enhance illumination. The best accuracies were obtained by the fine-tuned VGG-16 model, which achieved 99.01%, 97.25%, and 98.59% accuracies with classification times of 20.6, 20.7, and 35.9 msec for the date fruit type, maturity, and harvesting decisionclassificationmodels, respective

#### 9.FUTURE SCOPE

As for future work, we will improve the dataset by including testing images captured from different date orchards. We will also investigate more recent CNN models to minimize the usage of memory and lower computational complexity. One more area to investigate is the confusion in the maturity detection of date fruit, including labeling rules, and the interference among maturity stage

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