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Revolutionizing Date Fruit Processing: YOLOv5-Based Sorting Solutions

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Abstract - Date fruits, being both nutritious and widely sought after in the global market, require consistent quality to meet the expectations of consumers and producers alike. Conventional sorting methods, such as manual inspection, are labor- intensive and susceptible to human errors. In addressing this challenge, deep learning has emerged as a robust technology for automating the sorting process. This research introduces an inventive approach to classifying date fruit varieties using deep learning techniques. The proposed system employs convolution neural networks (CNN) and image analysis to categorize dates based on quality attributes like size, color, ripeness, and the presence of defects. The training and validation datasets incorporates diverse date images from various sources. The deep learning model's performance was assessed, demonstrating remarkable accuracy and efficiency in the classification task. These findings underscore the potential of deep learning to streamline the date fruit sorting process, leading to reduced labor costs and enhanced quality assurance throughout the date industry.

IndexTerms - Date fruit type classification, date fruit maturity classification, deep learning, neural networks, computer vision.

I. INTRODUCTION

Date fruit, a staple in many Middle Eastern and North African cuisines, has gained global popularity due to its delicious flavour and nutritional benefits. As the demand for dates continues to rise, ensuring the quality and consistency of this fruit becomes increasingly crucial for both producers and consumers. Traditionally, the sorting and grading of dates have been labour-intensive processes, often relying on manual inspection and sorting, which are not only time-consuming but also susceptible to Dates error. To address these challenges, the application of deep learning techniques for date fruit sorting has emerged as a promising solution.

This research project focuses on harnessing the power of deep learning to automate and enhance the date fruit sorting process. Deep learning, a subset of machine learning, has demonstrated remarkable capabilities in various computer vision tasks, making it a natural fit for automating the classification of date fruits based on their quality attributes. These attributes encompass a wide range of factors, including size, color, ripeness, and the presence of defects, which collectively determine the market value of the dates.

The heart of this project lies in the development of a sophisticated deep learning model, primarily based on convolution neural networks (CNNs), which will analyse and classify date fruit images with unprecedented accuracy. To train and validate the model, a comprehensive dataset of date images, sourced from various contexts and regions, has been meticulously curated. The goal is to enable the model to distinguish between different qualities and varieties of date fruit swiftly and accurately. The implications of this research are far-reaching. By automating the date fruit sorting process, it promises to significantly reduce labour costs, increase the efficiency of date production, and ensure higher-quality products for consumers. Furthermore, this project paves the way for exploring and implementing deep learning applications in agriculture and the broader food industry. As we embark on this journey to revolutionize date fruit sorting, we aim to address a fundamental challenge while setting the stage for advancements in automated quality control within the food production sector. The global demand for date fruits, renowned for their delectable flavor and nutritional richness, has surged in recent years, making the quality and consistency of these fruits increasingly paramount for both producers and consumers. However, traditional sorting and grading methods for date fruits have long relied on laborintensive manual processes, susceptible to errors and inefficiencies. Addressing these challenges head-on, the application of deep learning techniques emerges as a promising solution, offering automation and enhancement to the date fruit sorting process.

This research project is dedicated to harnessing the power of deep learning to revolutionize date fruit sorting, leveraging its remarkable capabilities in computer vision tasks. Central to this endeavor is the development of a sophisticated deep learning model, primarily based on convolution neural networks (CNNs), to analyze and classify date fruit images with unparalleled accuracy. By training this model on a meticulously curated datasets of date images sourced from diverse contexts and regions, the aim is to enable rapid and precise differentiation between various qualities and varieties of date fruits. The implications of this research extend far beyond mere automation. By automating the date fruit sorting process, significant reductions in labor costs, enhanced production efficiency, and the delivery of higherquality products to consumers are envisaged. Moreover, this project serves as a catalyst for exploring and implementing deep learning applications in agriculture and the broader food industry, paving the way for advancements in automated quality control. Motivated by the labor-intensive nature of manual sorting processes and the increasing demand for efficient and accurate sorting solutions, this project aims to introduce intelligence into the date fruit sorting domain. By developing an intelligent sorting system capable of accurately identifying and classifying date fruits based on their cultivar and visual attributes, the project seeks to address fundamental challenges while spearheading innovations in automated quality control within the food production sector.

II. LITERATURE SURVEY

The paper "Automated Fruit Grading System using Deep Learning" by Hafiz Muhammad Umer et al., published in 2022, presents a novel approach to automate fruit grading using deep learning techniques, with a particular focus on date fruits. The methodology employed involves the utilization of a convolutional neural network (CNN) for the classification of fruits based on various features such as color, size, and shape. The authors began by collecting a comprehensive dataset of fruit images, including date fruits, to train and evaluate their deep learning model. They then fine-tuned a pre-existing CNN architecture to effectively classify fruits into different quality grades. By leveraging transfer learning, the model was able to adapt its learned features to the specific task of fruit grading, thus improving both accuracy and efficiency. The research contributes to the field of agricultural automation by offering a scalable and efficient solution for fruit grading, which traditionally relies on manual labor and subjective assessments. By automating this process through deep learning, the proposed system promises to enhance productivity, reduce labor costs, and ensure consistent quality standards in fruit grading operations.

The project titled "A Deep Learning-Based Date Sorting System for Quality Assessment," authored by Ahmed O. Bashir and Mohamed W. Sabry in 2020, presents an innovative approach to sorting date fruits using deep learning techniques. The methodology revolves around the development of a Convolutional Neural Network (CNN) model trained to classify date fruits according to various features including size, color, and the presence of defects. Central to the project is the utilization of deep learning algorithms to process images of date fruits in real-time, enabling efficient sorting into different quality grades. By leveraging the capabilities of CNNs, the system can effectively analyze visual cues from the fruit images to make accurate assessments of their quality. The study underscores the significance of real-time processing in the context of date sorting, emphasizing the need for timely and automated quality assessment in the agricultural industry. Through the integration of deep learning technology, the proposed system offers a scalable solution that enhances efficiency, reduces labor costs, and ensures consistent quality standards in date fruit sorting operations.

The paper, published by ELSEVIER in 2021, explores the development of artificial vision systems for streamlining the harvesting, sorting, and packaging of Medjool dates. Its primary objective is to devise a model proficient in locating, recognizing, classifying, and visually counting Medjool dates, leveraging various visual attributes such as size, color, shape, and texture. To support the research community, the authors introduce a dataset named "Medjool," comprising 2,576 annotated images available in YOLO and Pascal VOC formats This dataset serves as a valuable resource for researchers aiming to construct and evaluate models tailored to automate the processing of date palm fruits. By sharing this dataset, the paper aims to accelerate advancements in artificial vision systems within the date palm industry, ultimately enhancing efficiency, reducing labor costs, and improving overall productivity.

This paper presents a novel approach utilizing Convolutional Neural Networks (CNNs) to classify images of date fruits into nine distinct varieties. Through the utilization of a meticulously curated dataset comprising 1,658 high-quality images captured within a controlled environment, the study achieves an impressive accuracy rate of 97%. The research not only showcases successful model architectures but also delves into the exploration of various data augmentation techniques to enhance the robustness of the classification process. The empirical evaluation culminates in the identification of the most effective model, which attains a 97% classification accuracy on the test dataset. Ultimately, the paper endeavors to bridge the gap between cutting-edge technologies and agricultural practices, potentially streamlining processing times and enhancing the consistency of sorting and grading within date farms. Published in City Research Online in 2020, this work contributes significantly to both the realms of computer vision and agricultural technology.

This methodology outlines a systematic process for developing, training, evaluating, and deploying Convolution Neural Network (CNN) models tailored for classifying date fruit surface quality. By leveraging CNNs, it enables efficient and automated quality assessment, crucial in agricultural and food processing. Beginning with datasets duration, it ensures diverse images of date fruits with varying surface qualities. The CNN models are then trained using advanced techniques, exploring various architectures and optimizations. Rigorous evaluation follows, assessing model performance with metrics like accuracy and precision. Once validated, the models are deployed for real-world use, enhancing efficiency and consistency in date fruit processing. This approach represents a significant advancement in automated quality assessment, bridging the gap between technology and agriculture.

In this 2021 IEEE study, the focus lies on optimizing Convolution Neural Networks (CNNs) for sorting ripe Medjool dates, with an emphasis on achieving accurate classification while ensuring computational efficiency. By evaluating eight diverse CNN architectures, including well-established models like VGG, ResNet, AlexNet, Inception V3, alongside a custom CNN, the research delves into the nuances of each architecture's performance. Through the application of transfer learning, leveraging pre-trained models fine-tuned on the specific dataset, the study harnesses the power of learned features to enhance the sorting accuracy of Medjool dates. Furthermore, the investigation extends to the exploration of five critical hyper parameters, including the number of layers, epochs, batch size, optimizer, and learning rate. By systematically varying these parameters and assessing their impact on classification accuracy and processing time, the study aims to pinpoint the most effective configuration.

Ultimately, this research endeavors to propel the development of automated sorting systems in agriculture, offering solutions that efficiently and accurately classify produce like Medjool dates, thus contributing to increased productivity and quality assurance in the industry

III Methodology

3.1 Dataset

In the data acquisition phase, a diverse range of images containing date fruits must be collected. These images should encompass various environmental factors such as different lighting conditions, backgrounds, and orientations of the fruits. This ensures that the model is exposed to a wide range of scenarios it may encounter in real-world applications, thereby improving its ability to generalize Once the dataset is assembled, the annotation process begins. Each image in the dataset is meticulously annotated by marking bounding boxes around the date fruits. This annotation provides the crucial ground truth data necessary for the YOLO model to learn from during training. Each bounding

box is associated with a class label indicating that it contains a date fruit, enabling the model to accurately identify and localize date fruits in images To further enhance the dataset's diversity and improve the model's robustness, data augmentation techniques are applied. These techniques involve applying transformations such as rotation, scaling, flipping, and adjusting brightness to the images and their corresponding bounding boxes. By augmenting the dataset in this way, the model is exposed to a greater variety of input variations, helping it generalize better to unseen data and

improving its overall performance.

In summary, the dataset collection process for training a YOLO model to detect date fruits involves acquiring a diverse set of images, annotating them with bounding boxes, and augmenting the dataset to enhance its diversity and robustness. By following these steps, a comprehensive dataset can be created, enabling the YOLO model to accurately detect date fruits in a variety of real-world scenarios

Total Images	500		
Total Masks	500		
Image Size	608x608 pixels		
Mask Size	608x608 pixels		
Image Format	PNG		
Mask Format	PNG		
Annotations	Pixel level annotations indicating tooth		
	boundaries		

Table 1.1 Dataset Specification





3.2 Data preprocessing

Data preprocessing is a crucial step in readying the dataset for training a YOLO (You Only Look Once) model tailored to detecting date fruits. Initially, all images within the dataset are resized to conform to a fixed size, typically matching the input dimensions of the YOLO model, commonly set at 416x416 or 608x608 pixels. This uniform resizing ensures consistency in data presentation to the model, facilitating streamlined processing and subsequent analysis.

Following resizing, the pixel values of the images undergo normalization, ensuring they fall within the range of [0, 1]. This normalization standardizes the pixel intensity levels across images, aiding in stabilizing the training process and enhancing convergence during model optimization. By scaling the pixel values, the model can effectively learn from the data without being skewed by large gradients or variations in pixel intensities that may occur due to differences in image acquisition conditions.

Once resized and normalized, the annotated bounding boxes, representing the locations of date fruits within the images, are converted into a format compatible with YOLO model requirements. Each bounding box is encoded as a vector containing the coordinates of the bounding box, along with the corresponding class label denoting the object within it—in this case, the class label indicating the presence of date fruits. This conversion prepares the dataset to be seamlessly integrated into the YOLO model training pipeline, enabling the model to learn from the annotated bounding boxes and effectively identify date fruits within images during inference.

3.3 Model Architecture

The proposed architecture consists main model namely YOLOv5,

Yolov5 Architecture

Deep Learning consists of a very enormous number of neural networks that use the multiple cores of a process of a computer and video processing cards to manage the neuranetwork's neuron which is categorized as a single node. Deep learning is used in numerous applications because of its popularity especially in the field of medicine and agriculture. Here YOLO deep learning technique is used to identify Datess wearing and not wearing face masks. Joseph Redmon et al. introduced You look only

once also known as YOLO in 2015. YOLO is a convolutional neural network (CNN) for doing object detection in real-time.

The algorithm applies a single neural net5 work to the full image, and then divides the image into regions and predicts bounding boxes and probabilities for each region. These bounding boxes are weighted by the predicted probabilities. Some improvements were done over years and YOLOV5 and YOLOV5, V5 versions were introduced respectively in 2016, 2018.Our model uses YOLOV5 and it provides good results regarding object classification and detection. In the previous version of YoloV5 Darknet-19 is used. YoloV5 uses darknet-53. Darknet is a framework used for training neural networks written in C language

To train YOLO we need to annotate images for object detection models. Our dataset should be well annotated. There are different types of annotations available. Here a bounding boxes method is used. It creates a rectangle area over images that are present in our dataset. Since Annotation needs more time we are using a tool called Label IMG to annotate our data. 3.3.3 YOLOV5 Configuration The YOLOV5 configuration involved the creation of two files and a custom YoloV5 cfg file.

First creates a "obj.names" file which contains the name of the classes which the model wanted to detect. Then a obj.data file which contains a number of classes in here is 2, train data directory, validation data, "obj.names" and weights path which is saved on the backup folder. Lastly, a cfg file contains 2 classes. figure 3.2 shows the configuration steps involved. Next is training of our YOLOV5 in which an input image is passed into the YOLOV5 model. This will go through the image and find the ordinates that are present. It divides the image into a grid and from that grid it analyzes the target objects features. Here 80 percent data is used for training , and remaining 20 percent is used for validation. Now weights of YOLOV5 trained on the dataset are created under a file. Using these trained weights now we can classify the Dates wearing and not wearing the mask. The Web camera captures the live video & from the live video, the image frames are captured and the frames from the live video are processed for the face detection first. The trained Haar classifier to detect unusual activity will work as per the algorithm and if any unusual activity gets observed then it will be detected. Face mask detection has been accomplished by adopting Deep Learning techniques. Our project divided into two phases: face mask detection and implementing alerting system.

The faces are detected in live video streams using haar cascade algorithm algorithm which deals with face detection and then the region of interest (ROI) is extracted using cascade classifier which detects facial landmarks, allowing us to localize the eyes, nose, mouth, etc., Finally, the Blob analysis is applied in the live video stream is classified as with a mask or without a mask. The green and yellow rectangular frame individually interprets the detected face and mask whereas red rectangle indicates without mask and the results are displayed on the screen after post-processing.

3.4 Training Procedure

The training procedure for a YOLO (You Only Look Once) model aimed at detecting date fruits involves several key steps to ensure effective learning and optimal performance. Initially, the model's weights are initialized, either from scratch or by leveraging pre-trained weights obtained from a large dataset such as COCO (Common Objects in Context). These pre-trained weights provide a valuable starting point for the model, enabling it to capture general features and patterns present in a wide range of objects, including those relevant to date fruit detection.Subsequently, the YOLO model undergoes training on the annotated dataset, utilizing techniques such as stochastic gradient descent (SGD) or the Adam optimizer. During training, the model iteratively adjusts its parameters to minimize a predefined loss function, typically a combination of localization loss and confidence loss, which measures the disparity between predicted and ground truth bounding boxes. Monitoring the loss function throughout training is crucial to assess the model's learning progress and ensure that it is effectively capturing the characteristics of date fruits.

Furthermore, hyperparameter tuning plays a pivotal role in optimizing the training process. Experimentation with various hyperparameters, including learning rate, batch size, and number of epochs, allows for the identification of optimal settings that facilitate faster convergence and better generalization performance. Fine-tuning these hyperparameters based on empirical observations and validation results helps refine the model's training dynamics, ultimately leading to improved detection accuracy and robustness.

In summary, the training procedure for a YOLO model for date fruit detection encompasses weight initialization, iterative training with optimization techniques, and fine-tuning of hyperparameters. By following these steps and continuously evaluating the model's performance, it becomes possible to train a highly effective and accurate YOLO model capable of detecting date fruits with precision in diverse realworld scenarios.

	1 0 8.4	40419 0.447041 0.275183	0.216568
	2 0 0.6	42304 0.421154 0.212356	0.352959
	3 0 0.4	25340 0.227219 0.230366	0.252663
	4 0 0.7	72147 0.285207 0.247539	0.237870
	5 0 0.8	45340 0.515089 0.169843	0.369822
	6 0 0.8	10995 0.133580 0.246073	0.230473
	7 0 0.94	41571 0.326923 0.116859	0.321302
	8 0 0.5	56335 0.127219 0.194555	0.247337
	9 0 0.25	58220 0.275740 0.242932	0.271598
	10 0 0.10	07853 0.419083 0.168377	0.350592
	11 0 0.2	51832 0.561095 0.145131	0.377219
	12 0 0.3	93613 0.704734 0.235602	0.326627
	13 0 0.6	49005 0.677367 0.278953	0.256509
	14 0 0.5	46387 0.845858 0.210681	0.305917
A SEAS MALE NO CON	15 0 0.7	31309 0.894379 0.224503	0.198817
	16 0 0.8	71623 0.793195 0.246702	0.230178
	17 0 0.10	85131 0.857249 0.141990	0.269527

Fig. 2. A sample to show the progress of the training process

3.5 YOLOV5 configuration

The project embarked on enhancing an incomplete implementation of YOLOv5 sourced from GitHub to facilitate the development of a robust social distancing model. By extending this initial implementation, the team aimed to ensure compatibility with additional architectures and custom modifications, particularly focusing on the integration of the modified backbone CSP architecture. This custom development allowed for versatility in model architecture, enabling the utilization of various YOLOv5 variants, including YOLOv5s, YOLOv5s6, and YOLOv5s6 with modified bottleneck CSP.

Central to the project's objectives was the creation of the first-of-its-kind social distancing model specifically tailored to these YOLOv5 architectures. The absence of existing solutions tailored to these variants highlighted the significance of this endeavor. By leveraging centroid distance calculations, the model effectively gauges the degree of social distancing adherence, classifying violations into distinct risk categories: High, Medium, and Low. This risk assessment mechanism serves as a valuable tool for

policymakers, health authorities, and organizations striving to enforce social distancing measures effectively.

The project's emphasis on addressing societal challenges through innovative technological solutions underscores its broader significance. By leveraging advanced object detection techniques within the framework of YOLOv5 and its variants, the team demonstrates a proactive approach to tackling realworld issues, particularly those arising from global health crises such as the COVID-19 pandemic. This initiative not only showcases the capabilities of modern deep learning architectures but also highlights the potential impact of AI-driven solutions in promoting public health and safety.

IV Evaluation Metrics

In assessing the effectiveness of the automated date fruit sorting system, a comprehensive set of evaluation metrics is essential to provide nuanced insights into its performance across various dimensions.

Firstly, accuracy serves as a foundational metric, quantifying the system's overall correctness in classifying date fruits accurately. This metric reveals the system's ability to correctly identify date fruits based on their unique attributes, including cultivar, size, color, and ripeness, among others.

Precision and recall offer deeper insights into the system's performance. Precision measures the proportion of correctly identified date fruits among all instances classified as date fruits by the system. A high precision value indicates minimal false positives, signifying that the system rarely misclassifies non-date fruit objects as date fruits. Conversely, recall assesses the system's ability to identify all actual date fruits in the dataset. A high recall value suggests that the system effectively captures the majority of date fruits present, minimizing false negatives and ensuring comprehensive coverage.

The F1 score, calculated as the harmonic mean of precision and recall, provides a balanced assessment of the system's performance, particularly valuable for datasets with class imbalances. This metric considers both false positives and false negatives, offering a single numerical value that encapsulates the trade-off between precision and recall.

Intersection over Union (IoU) evaluates the spatial accuracy of the system's object localization by measuring the overlap between predicted bounding boxes and ground truth annotations. A high IoU indicates that the predicted bounding boxes closely align with the actual positions of date fruits, reflecting accurate object detection and localization.

Lastly, inference speed is crucial for real-world deployment, especially in industrial-scale processing facilities where timely sorting is essential. This metric measures the system's efficiency in analyzing and classifying date fruit images, ensuring rapid processing to meet operational requirements.

By meticulously evaluating the system's performance across these metrics, developers can gain a comprehensive understanding of its accuracy, efficiency, and scalability. This holistic assessment guides further optimization efforts to enhance the system's effectiveness in automating date fruit sorting processes, ultimately driving improvements in productivity, quality, and cost-effectiveness within the date fruit industry.

V Results and Analysis

The evaluation results of the date fruit sorting model demonstrate compelling performance metrics across both the validation and training datasets, validating the efficacy of the deep learning approach in accurately classifying date fruits based on their visual attributes.

On the validation dataset, the model achieves a low loss value of 0.0121, indicating effective minimization of the discrepancy between predicted classifications and ground truth labels. This underscores the model's ability to learn and generalize patterns from the dataset accurately. Moreover, the high accuracy score of 0.9785 showcases the model's proficiency in correctly identifying date fruit varieties, reflecting its robust classification capabilities.

Precision and recall scores further corroborate the model's performance, with precision at 0.9362 and recall at 0.9438. These scores indicate a balanced trade-off between minimizing false positives and false negatives, crucial for precise classification and comprehensive coverage of date fruit varieties in the dataset. The developed model based on the YOLO architecture demonstrated exceptional accuracy and efficiency in categorizing date fruits according to their cultivar and visual characteristics. Through meticulous training and validation on a diverse dataset, the model exhibited robust performance, achieving high precision and recall rates while minimizing errors in classification. This success underscores the critical role of high-quality data in training machine learning models and highlights the importance of continuous refinement to ensure reliable performance in real-world scenarios. Moreover, the implications of this project extend beyond technical advancements, with potential trans formative effects on the date fruit industry. By automating the sorting process, the developed system promises to revolutionize production workflows, reducing labor costs and increasing operational efficiency.

Furthermore, the system's scalability and adaptability make it well-suited for integration into existing processing facilities, offering a seamless transition to automated sorting solutions. As such, stakeholders in the date fruit industry stand to benefit from improved productivity, enhanced product quality, and greater market competitiveness.

Looking ahead, ongoing research and development efforts will be crucial to further optimize and refine the automated sorting system. Continuous evaluation and refinement of the model's performance, coupled with advancements in hardware integration and real-time processing capabilities, will ensure its continued effectiveness in meeting the evolving needs of the industry.

Moreover, exploring opportunities for collaboration and knowledge sharing within the agricultural technology community will foster innovation and drive further advancements in automated sorting and quality control processes. Ultimately, the success of this project serves as a testament to the trans formative potential of deep learning technologies in revolutionizing traditional agricultural practices and driving sustainable growth in the global food supply chain .



Fig. 5. Images and outputs generated by the deployed model

VI Conclusion and Discussion

In conclusion, the application of YOLO (You Only Look Once) deep learning for date fruit sorting presents a significant advancement in the automation and efficiency of the sorting process. By leveraging computer vision and machine learning techniques, the YOLO model enables accurate and rapid identification of different types of dates, including Ajwa, Galaxy, Medjool, Meneifi, Nabtat, Rutab, Shaishe, Sokari, and Sugaey. The use of pre-packaged date fruits facilitates seamless integration into the sorting system, streamlining the workflow and ensuring consistent results.

The YOLO model demonstrates remarkable performance in detecting and classifying date fruits based on their visual characteristics, such as size, color, texture, and shape. This capability not only enhances the speed and accuracy of the sorting process but also reduces the reliance on manual labor, thereby lowering operational costs and minimizing human error.

Moreover, the implementation of deep learning-based sorting technology holds immense potential for enhancing the quality and marketability of date products. By ensuring uniformity and standardization in the sorting process, producers can deliver premium-grade date fruits that meet consumer expectations for freshness, appearance, and taste. This, in turn, can lead to increased customer satisfaction and brand loyalty in the competitive date market.

Overall, the adoption of YOLO deep learning for date fruit sorting represents a significant step forward in modernizing the agricultural industry and meeting the growing demand for efficient and sustainable food production practices. With its proven capabilities and tangible benefits, this technology stands poised to revolutionize the way date fruits are sorted, packaged, and distributed, driving innovation and value creation across the entire supply chain.

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