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AI/ML Drone-based Arecanut Monitoring System (ADAMS)

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ABSTRACT

The Indian economy relies heavily on agriculture with 72% of farmers in the states of Karnataka and Kerala producing 330 million kilograms of arecanuts. However, a rapid increase in young adults leaving the agriculture field brings hardships for older farmers like my grandparents since physical labor is increasingly expensive, dangerous, and scarce. The purpose of this research is to automate arecanut crop monitoring by providing a safe, affordable, user-friendly, and cutting-edge system that utilizes six major elements to achieve the goal: arecanut farm, drone, dataset collection, data annotations, AI/ML Mask R-CNN prediction model, and app. Research about various drones were conducted to ensure the drone abides by Indian UAV regulations. Since there were no pre-existing arecanut datasets, a DJI Mini 2 drone and Canon DSLR Camera were utilized to capture over 2000 arecanut images in India. Creating my own dataset from scratch was challenging, however it was a significant contribution in advancing computer vision. This dataset was stored on Amazon S3 and classified into ripe, unripe, and dry arecanuts. Each image was manually annotated using VGG Image Annotator and passed into a Convolutional Neural Network called Mask R-CNN to create a prediction model. This was trained on Amazon Web Services (AWS) for 100 epochs. Overall, epoch 85 gave accurate predictions. Additionally, instead of the DJI Mini 2 drone, the Skydio drone would be the best option for real world implementations. My research is a practical and innovative solution to alleviate farmers' financial and physical hardships.

Introduction

India, the 2nd largest agricultural producer in the world, produces 330 million kilograms of arecanuts each year. Kerala and Karnataka, two states in India, cultivate 72% of India's arecanuts in a total area of 264,000 hectares of farming land (Anilkumar, M. G., 2021). However, maintaining and inspecting the large quantity of arecanuts is an enormous task for farmers like my grandparents who have to climb palm-like trees, around 10 to 20 meters tall, in order to examine the growth of arecanuts which are the size of golf balls.

Oftentimes, these arecanuts can be infected with a common disease called Mahali/Fruit Rot which is caused by a fungus-like eukaryote, *phytophthora meadii* or an oomycete (Ramesh, 2014). Oomycetes are often referred to as water molds because of their tendency to favor watery areas (William E. Fry, 2010). Some symptoms of this disease include the rotting and shedding of immature nuts from trees and white mycelial growth on the top of the nut (TNAU Agritech Portal, 2015). Fruit rot disease occurs annually in Malnad, Mysore, North & South Kanara, Malabar and other areas with similar monsoon seasons (Apeda, 2022). Once one arecanut fruit is infected, it can rapidly spread to other arecanut fruit bunches and trees, annihilating approximately 40-50% of crops.

Furthermore, the average age of a farmer has risen to 50 years old in India. Traditional methods of harvesting such as climbing tall trees are becoming increasingly dangerous due to the decrease in young able-bodied people (Mahapatra, 2020). Since farmers can't accurately check the growth of arecanuts without manual inspection, there is an irregularity in harvesting times. Harvesting the arecanuts at the right time is crucial to ensure high quality nuts. Unripe or semi-ripe arecanut fruits yield low grade nuts and tend to sell at lower prices. Additionally, late identification of diseases leads to significant crop loss and fewer good quality crops. At the same time, wages for workers are increasing rapidly and many small farmers can't afford to pay their workers. Due to these reasons, farmers face huge financial and physical hardships.

Arecanut Farms and Arecanuts

Arecanuts, also known as betel nuts, are cultivated in India and South East Asia. An arecanut farm consists of tall palm-like trees towering on average between 10 to 20 meters with golf-ball sized arecanuts located right under the canopy. Arecanut trees are planted in rows and start to give off fruit in their 5th to 7th years all the way up to 60 years. Arecanut fruits are oval in shape and when ripe they are orangish-red in color. They thrive in climates with temperatures around 14 to 36 degrees Celsius and abundant rainfall. Additionally, arecanut farms can consist of other intercrops such as black pepper, cocoa, banana, papaya and pineapple (The Hindu BusinessLine, 2018).

The life cycle of an arecanut starts off as white flower-like tendons sprouting from the tree. Then after a few months it produces green unripe arecanuts. From December to February, the arecanuts are orangish-red in color indicating that it is harvesting time. Then the fruit needs to be dried and husked to reveal the nut. The drying process takes place in the summer/heat season in India.

Arecanuts grow in rings around the tree. The first batch grows in a cluster that can contain 50 or more arecanuts. Then a few weeks later the second batch of arecanuts starts to grow a few inches above the initial batch. Each batch matures at approximately the same time. As a result, during the harvesting season, multiple rounds of harvesting need to be done depending on how many "rings" or batches of arecanuts are on the trees.

Figure 1. Arecanut farm and arecanuts. The above photo shows a typical arecanut farm at the top and the bottom three photos show unripe, ripe, and dry arecanuts.

Figure 2. Arecanut Bunches on an Arecanut Tree. The image above shows a typical arecanut tree with multiple bunches of arecanuts.

Engineering Design and Flowchart

To address this problem, the project is divided into 6 overarching parts: Arecanut Farm, Drone, Data Collection, Data Preparation and Annotation, AI/ML Mask R-CNN Prediction Model, and smartphone app. A high-level description of the system is that a drone would capture arecanut images, send them to the cloud prediction model, and the results would be outputted on the smartphone app.

Drones are necessary to easily capture arecanut images because these golf-ball sized arecanuts are located in tall palm-like trees. It would eliminate the need for workers to perform hazardous tasks such as climbing trees.

The prediction model would be trained on a custom-made dataset with over 2000 images. These images were captured in January 2022. The prediction model is located on AWS and the images are stored on Amazon S3. The model will analyze arecanut images and predict if a given image contains ripe, unripe, or dry arecanuts.

The app serves as a connector between the images captured on the drone and the prediction model in the Cloud. Additionally, it will present the results from the prediction model to the user in an organized way. It facilitates image transfer and presentation of results.

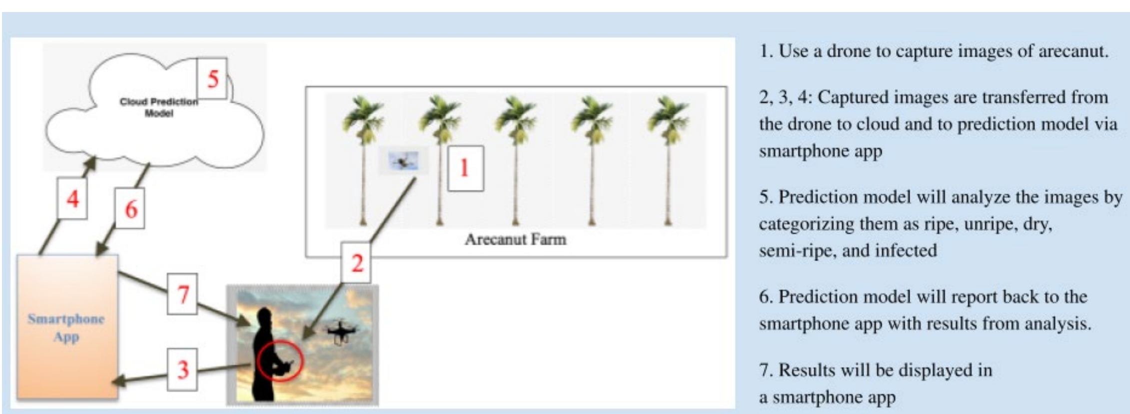

Figure 3. Engineering Design. The image above shows the flowchart for this research project.

Methods

Prediction Model

A Mask R-CNN prediction model was used for this research. Mask R-CNN is much more efficient that its predecessors such as Faster R-CNN or Fast R-CNN (Xueping Ni, 2020). Mask R-CNN was developed in 2017 and was a revolutionary improvement in Convolutional Neural Networks (CNN) because of its ability to perform instance segmentation. Instance segmentation combines object detection and semantic segmentation. Object detection is able to detect that an object is present, but not the exact pixel values. Semantic segmentation can identify the object pixels. When combined together, instance segmentation can detect that an object is present, detect the exact pixels associated with that object, apply a bounding box around the object, and apply a mask or a transparent sheet of color over the object to help viewers easily visualize the output.

Data Collection and Annotation

A large dataset is required to get the most accurate predictions from the prediction model. To acquire this large dataset, a DJI Mini 2 drone and a Canon DSLR camera were used to capture over 2000 images of ripe, unripe, and dry arecanuts. I captured these images in January, 2022. Additionally, many different camera angles (front, back, above, below) and backgrounds (trees in the background, black ground, red ground) were used.

Unfortunately, due to COVID-19, I was not able to go to India in July/August to collect data of arecanuts with Mahali/Fruit Rot disease. However, using the same picture capturing techniques mentioned above, the infected arecanuts can also be trained in the prediction model given sufficient data.

Another important step in preparing the data is data annotation. The prediction model needs a dataset with annotations on it for the training process. From these images, the model will learn to detect those certain objects. Annotations are like placement markers for the model. The model can read the annotations in order to figure out the shape and color of an arecanuts so that when it is given testing data it can correctly identify the arecanut and its condition. Annotating the images puts bounding boxes or bounding polygons around the object. VGG Image Annotator (VIA) was used for this process. The annotations were done using polygons and exported as a json file. The tedious task took 7 days to complete because the images were all manually annotated.

Drone Selection

A drone feature comparison table was made to compare different features of the drone. The drone had the most factors to consider. Some weather factors that affect drones are wind, rain, and sun. A drone cannot fly in the rain because it is not waterproof and the rain water could damage it. Strong winds could cause the drone to swerve off course which may make retrieval of the drone tough. It can also cause the drone to shake while it is taking the images of the arecanuts, causing a poor image quality. Too much sun can cause the drone to overheat.

Another important factor considered was the height of the arecanut tree. Adult arecanut tree heights can range from anywhere between 10 to 20 meters. Any drone used for this project should be able to reach that height.

Additionally, the drone had to abide by Indian UAV regulations. The rules stated that nano drones (<250g) could be flown to 15 meters high. Indian UAV rules categorize drones as nano (<250g), micro (250g-2kg), small (2-25kg), medium (25-150kg), and large (150+ kg) (Ministry of Civil Aviation, 2021).

Results

Drone Feature Comparison Table

Table 1. Displays important information about different drones. The different features are compared to identify the best drone for this research.

Drone	Weight (grams)	Cost	Obstacle Avoidance/Sensing	Flight Time (minutes)	Max Flight Height (meters)	Max Flight Distance (no wind) (km)
DJI Mini 2	249	$449	Yes. Downward	31	500	16
DJI Air 2s	595	$999	Yes. Forward, backward, upward, downward	31	500	18.5
Mavic Air 2	570	$799	Yes. Forward, backward, downward	34	500	18.5
Phantom 4 Pro V2.0	1375	$1599	Yes. Forward, backward, downward, lateral	30	500	8
DJI Mavic 3	895	$2199	Yes. Forward, backward, upward, downward, lateral	46	500	30
Skydio 2+	800	$1099	Yes. 360 degrees	27	499	6
Autel EVO Nano+	249	$949	Yes	28	800	9
Parrot Anafi	320	$499	Yes	25	150	4

Prediction Model

A couple test images were used in order to measure the accuracy of the prediction model. The following images show five graphs where two graphs are divided into Set 1 and three graphs are divided into Set 2.

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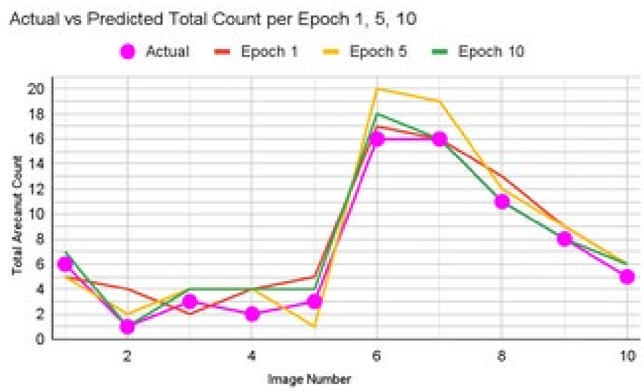

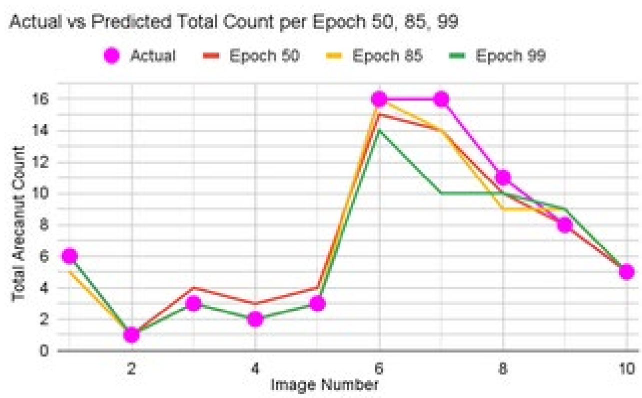

Figure 4. Set 1. The image above shows the comparison between the actual number of arecanuts per photo versus the number of arecanuts the different epochs of the prediction model predicted to be in that photo. The epochs tested in set 1 are 1, 5, 10, 50, 85, and 99. The actual number of arecanuts per photo were determined by counting manually.

From the set of graphs above, the graph with epochs 50, 85, and 99 seem to follow the actual number of arecanuts curve more accurately. Set 2 provides a closer look at these epochs in comparison to the maturity level of the arecanut.

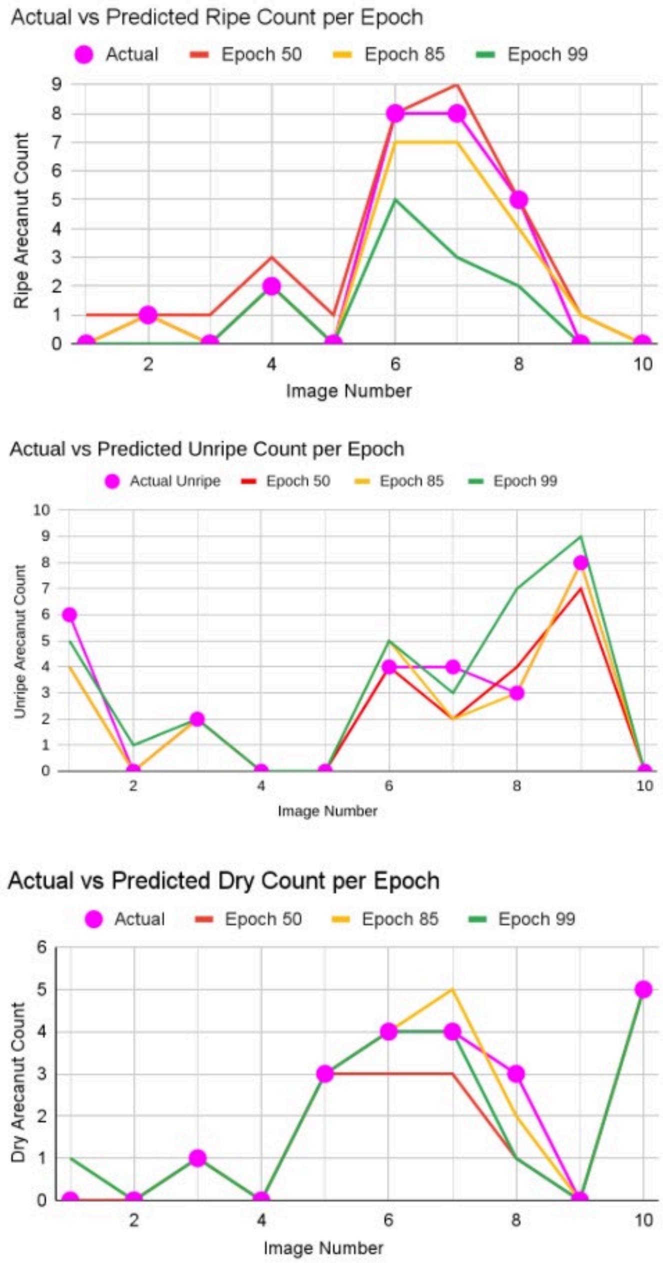

Figure 5. Set 2. The image above shows the comparison between the actual number of ripe, unripe, dry arecanuts per photo versus the number of ripe, unripe, dry arecanuts the different epochs of the prediction model predicted to be in that photo. The epochs tested in this set are epoch 50, 85, and 99. The actual number of arecanuts per photo were determined by counting manually.

The following images show sample results from the Mask R-CNN prediction model compared to several epochs. Green mask represents unripe, blue represents dry, red represents ripe, and purple represents semi ripe.

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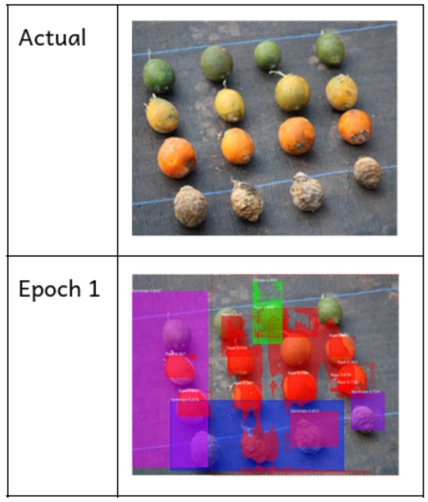

Figure 6. Actual and Mask of Epoch 1. This image shows how the actual photo of the arecanuts look versus what mask epoch 1 outputs.

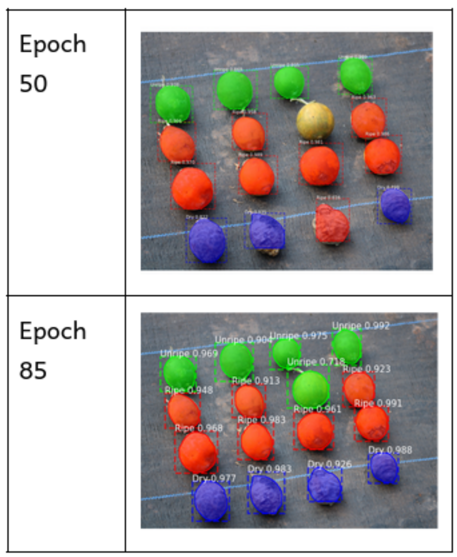

Figure 7. Mask of Epoch 50 and 85. This image shows what masks the prediction model for epoch 50 and 85 output.

Discussion

Drone Operation and Challenges

Some major variables of the drones to compare were obstacle avoidance, cost, size, flight height, battery time, and legality of flying it. Indian UAV rules categorize drones as nano (<250g), micro (250g-2kg), small (2-25kg), medium (25-150kg), and large (150+ kg). All drones except nano need a license. Skydio 2+ had the best obstacle avoidance mechanism and was light enough to fit Indian UAV regulations (micro category), however it was on the expensive side. DJI Mini 2 was the right size (nano category) and cheaper than Skydio drones, but it did not have robust obstacle avoidance mechanisms.

During the process of data collection, there were some operational challenges. Manually operating a drone is impractical. Maneuvering the drone between dense tree populated areas is a hassle without an efficient obstacle avoidance mechanism. The drone must have a built-in obstacle avoidance feature and GPS coordinate system. It will give the farmer more ease and flexibility. In India, a nano drone cannot fly over 15 meters. Although the height restriction is not a problem for most trees, some older trees can grow to be 20-25 meters tall. For those trees, a micro drone would be better. Micro drones cannot fly over 60 meters. This project used a nano drone as it is compact, light weight, and sufficient for a majority of trees.

There are some drawbacks when using drones. Direct sunlight can heat up the drone. Current micro drones cannot fly for more than 40 minutes. Video recording takes up a significant amount of storage space. In the DJI Mini 2 drone, 1 minute of video recording equated to around 1GB of video storage. Additionally, using a drone for farmers living near airports would be impractical due to the new drone laws stating that drones cannot be used near airports.

However, there are benefits to using drones. Taking pictures at 15 meters high is easy and the drone can take high resolution photos.

In the future, as drones implement more obstacle avoidance and autonomous designs in them, this project will be more feasible.

Prediction Model

There are two factors to be considered for the prediction model: object detection and instance segmentation. Object detection is the purpose of the first set of graphs. These graphs identify an epoch that can detect the correct number of objects in each of the 10 testing images. More epochs usually equal to more accuracy. As predicted, epoch 50, 85, and 99 had more accuracy than epoch 1, 5, and 10. Instance segmentation can detect an object pixel by pixel and give it the correct classification. In my research, I compared 3 classes: Ripe, Unripe, Dry. The 1st,2nd,3rd graph in the second set of graphs compares the actual vs predicted number of ripe, unripe, dry arecanuts respectively that epoch 50, 85, 99 detected. Places where the epoch line and pink dots don't meet indicate that the prediction model doesn't detect the correct number of ripe, unripe, or dry arecanuts in that particular image. I did expect the later epochs to predict results more accurately, however I didn't expect epoch 85 to be more accurate than epoch 99.

Conclusion

For the purpose of collecting arecanut images, the DJI Mini 2 was a good fit, however when implementing this in the real world the Skydio 2+ would be the best option because of its intelligent 360° obstacle avoidance feature and many other comparatively better features. Additionally, bigger farms would benefit economically from drones rather than smaller farms.

Epoch 50, 85, and 99 detected the arecanuts more accurately and precisely than epoch 1, 5, and 10. Moreover, epoch 85 could detect the number of ripe, unripe, and dry arecanuts more accurately than epoch 50 and 99.

Applications in the Real World

There are many applications for this research in the real world. This research is not constricted to only arecanuts. This technology can be used for other crops. It also may be deployed in numerous South East Asian countries where there are a large number of arecanut farms. Currently, my prediction model can identify proper unripe, ripe, and dry arecanut conditions. This will help farmers figure out if their crops are ready to be harvested so that they can prevent untimely harvesting. Additionally, it can be expanded to detect various arecanut diseases like Mahali/Fruit rot, bud rot, etc. This research can be expanded to identify trees with infected nuts so that farmers only need to spray that specific tree with pesticides. This helps minimize the use of pesticides in order to help the environment and prevent pesticide runoff and pollution. On a broader note, it can also help with animal control. It could detect the presence of animals disrupting crop growth through the images taken by the drone. This will help increase the efficiency of the farm.

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