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Tree Crown Detection using UAV-captured High-Resolution Aerial Images for Baghdad University Campus

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Abstract The research paper's objective is to develop an automated system that uses high-resolution aerial images captured by Unmanned Aerial Vehicles (UAVs) to accurately detect and analyze tree crowns on the Baghdad University campus. This analysis of tree crowns is crucial for assessing vegetation health and distribution in urban areas, with applications in urban planning, ecology, and environmental studies. The proposed system utilizes computer vision and machine learning techniques to detect and delineate tree crowns, facilitating objective analysis of tree canopy coverage. The study employed a Phantom Four drone flying at a height of 55 meters with an 80% overlap in image coverage. Ground control points were established using the Topcon_HIPER2 device and Static GPS Surveying Techniques. The flight plan was designed with PIX4Dcapture software, and the resulting ortho-map had a 2 cm resolution. The research used the YOLOv3 artificial intelligence technique for tree detection after training a customized dataset. The model achieved impressive performance metrics, including a low loss function value of 0.023, a high SDC value of 0.984, and a robust Jaccard Index value of 0.943.

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Keywords: *UAVs, Ortho-Map, Tree Detection, GCP, Yolo V3*

1. INTRODUCTION

Tree forests and green spaces play a crucial role in achieving environmental equilibrium and mitigating the proliferation of pollutants, climate change (Pretzsch, et al., 2017; Ali, Mahdi, Hussan, & Al-Azawi(b), 2012), and escalating temperatures. Given the significance of monitoring vegetation, changes in the structure of agricultural lands and forests (Allawai & Ahmed, 2020), and the identification of potential plant diseases (Neupane & Baysal-Gurel, 2021),prompt analysis and implementation of appropriate measures are imperative to enhance productivity. While various methodologies exist for studying these aspects, field-based approaches offer detailed data on trees and forests but are deemed costly and time-consuming, particularly in expansive regions. Consequently, the utilization of contemporary remote sensing techniques, notably aerial imagery (Mohan ،Silva ،ORCID و ، Jat؛2017 ، Difar و Abed2022 ،) (Midhun Mohan EMAIL logo, Broadbent, Jaafar, & Srinivasan, 2021)and satellite data (Mohammed, Ali, Mohammed, & Saeed, 2021; Mashee, Mutlag, & Rasheed, 2020; Mahdi, 2022; Abd-Alwahab & Ghazal, 2019; S.Ismaal, A.Alazaq, F.Rasheed, & F.Khanjer, 2018), has emerged as a viable substitute.. Unmanned aerial vehicles, in particular, facilitate the acquisition of highly precise spatial data in a timely fashion, enabling comprehensive and accurate land and crop analysis at a reasonable cost compared to alternative methods.

2. RELATED WORK

In recent years, there has been significant interest in the integration of drone data and artificial intelligence (AI) applications for the purpose of tree detection and plant classification. This section provides an overview of the scholarly literature that has been employed to study the detection of trees and the classification of plants using data obtained from unmanned aerial vehicles (UAVs).

- (Albattah, et al., 2022)**:** The study focuses on adopting an early approach to detect multiple diseases of plants using drones and artificial intelligence techniques. The methodology of the study utilized a low-cost Phantom 3 drone, with flight heights ranging between 3 to 6 meters. The study also utilized the plant village dataset, which contained a large number of leaves and crop diseases, as a basis for analysis. The results demonstrated the effectiveness of the proposed system for early detection of plant diseases, utilizing high-accuracy data obtained by the drone. Additionally, the study showcased the capability of artificial intelligence in identifying multiple categories of plant diseases.
- (Chen, et al., 2021)**:** The researchers introduced a novel approach for disease detection in trees, utilizing deep learning techniques applied to drone-collected data. The primary objective was to train deep learning algorithms to accurately identify infected plants. The integration of drone

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technologies and deep learning tools yielded promising results, showcasing a high level of accuracy in detecting both diseases and insects. This approach enables precise targeting and reduces the reliance on indiscriminate pesticide use, thereby mitigating associated risks.

➢ (Zheng, et al., 2021)**:** The researchers used drones to study the growth of palm oil trees. Including a set of characteristics of these trees such as leaf size, crown width and tree height. The researchers focused on developing a pre-processing methodology that included pre-processing, feature extraction, and model development. The data consisted of a set of high-resolution multispectral images taken over a field in Malaysia. The results showed the effectiveness of drone images for monitoring the growth of the oil palm tree, with high accuracy achieved in estimating tree height (R^2 = 0.89), crown width (R^2 = 0.83). , and LAI (R^2 = 0.81).

➢ (Al-Najjar, et al., 2019)**:** The researchers used unmanned aerial vehicle imagery and digital elevation models to characterize the land cover to improve land cover mapping. The classification was done using convolutional neural networks (CNNs) as the main methodology for land cover classification in this study. The data set is from aerial photographs and DSM models of the study area. The results showed the effectiveness of this approach based on the use of combined data for land cover classification, as it provided more comprehensive data compared to individual data sources.

3. PROBLEM STATEMENT

The main problem addressed in this research paper revolves around the following points:

1) The need to generate an ortho-map using high-resolution aerial data for the designated study area.
2) Establishing a comprehensive dataset specific to trees within the study area to train an artificial intelligence model capable of tree detection in the region.
3) Analyzing the suitability and efficacy of the selected data sources in terms of their ability to provide accurate and reliable data for this type of research.
4) Investigating the accuracy and potential adoption of these data sources as effective tools for tree detection and analysis in the study area.

4. STUDY AREA

The focal point of this study is the University of Baghdad, which stands as one of Iraq's oldest and most prestigious academic institutions. Situated in the Jadriya district in close proximity to the Tigris River, the university enjoys a strategic position at the heart of Baghdad (Figure 1), the capital city and one of Iraq's largest urban centers, geographically situated at the country's midpoint. Precisely, the University of Baghdad occupies a central location within the city, spanning an area between 33.3082 degrees north latitude and 44.3635 degrees east longitude on the western bank of the Tigris River. It comprises a consortium of multiple colleges, each contributing to the diverse academic landscape.

This research primarily focuses on the university's campus grounds, characterized by a rich and varied landscape adorned with a myriad of tree species and flora. Aerial photography, employed as a key tool in this study, encompasses the extensive college complex, enabling the comprehensive capture of tree canopies and other pertinent features.

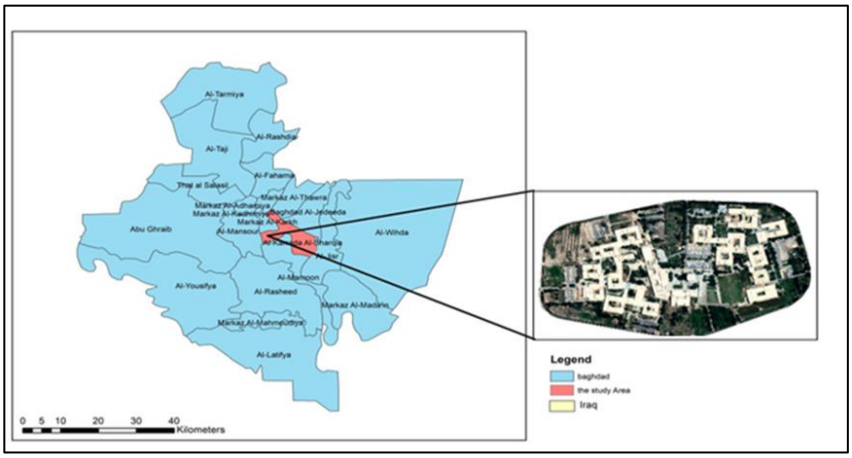

Figure 1*:Iraq, Baghdad City, and (University of Baghdad) Study Area's Maps*

5. RESEARCH METHODOLOGY

The utilization of drones in agricultural applications has experienced notable advancements and significant progress in recent years. This is attributed to the capability of these aerial vehicles to deliver timely and precise information at a reasonable cost compared to conventional methods. The methodology employed in this study aims to harness the potential of drones to construct an ortho map of the designated study area. Furthermore, this data will be

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employed to facilitate tree detection within the area through the implementation of artificial intelligence techniques. Figure 2 provides a concise overview of the methodology employed in this research endeavor.

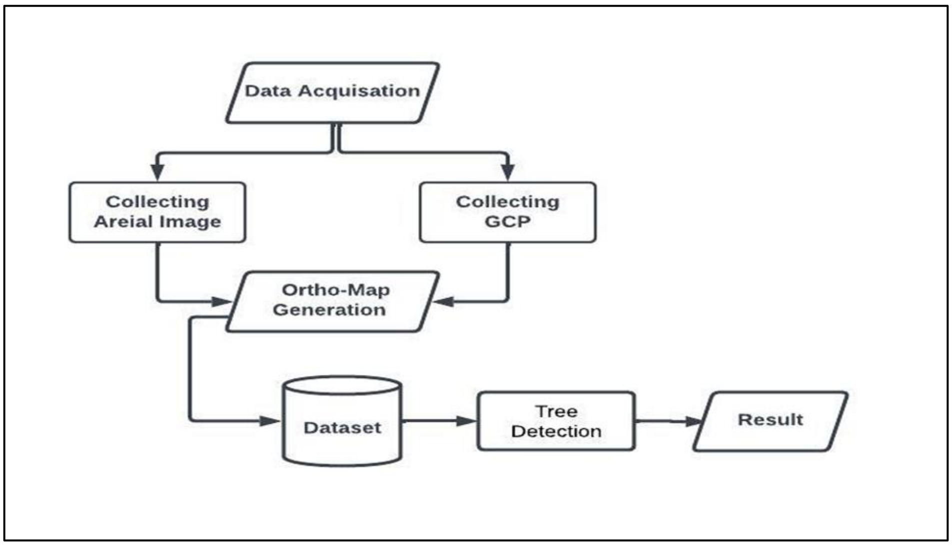

***Figure 2**: Block diagram of the current research work steps*

5.1. Data Acquisition

The data acquisition process in this study involved two distinct phases, namely the collection of ground control points from the study area and the acquisition of images using a drone within the designated area of interest. This section aims to provide a comprehensive explanation of the data collection methodology employed in this research.

5.1.1 Collect Ground Control Points

In the process of building aerial maps, the work field should contain ground control points before starting the data collection process. These points help confirm the geographical reference of the resulting map (Park & Yeom, 2022). A group of ground control points was collected using the Topcon_HIPER2 device. Ground control points were established and marked with targets in this study so that they appear clearly in the resulting map, which makes it easier to identify them later, as shown in Figure (3). The size of the targets must be proportional to the flight altitude in a way that ensures that they can be identified in the map results.

***Figure 3**:Collecting Ground Control Point Using DGPS*

To ensure accuracy and adequate coverage in the study area. Seven ground points were distributed in different locations within the study area. The spatial distribution of these points is shown in Figure (4).These points are distinguished by targets during the collection of images, and consideration must be given to the possibility of distinguishing these targets in the resulting: map in a way that facilitates the comparison

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of the coordinates of these points in the resulting map with the coordinates of the ground control points (Figure5).

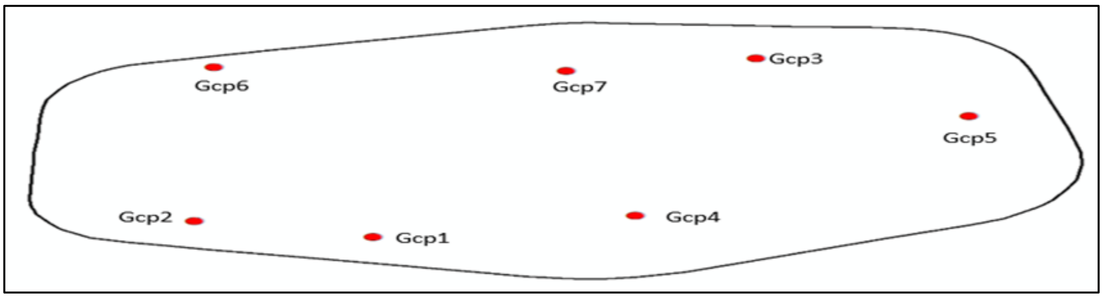

Figure 4:The Distribution of Ground Control Points in the Study Area

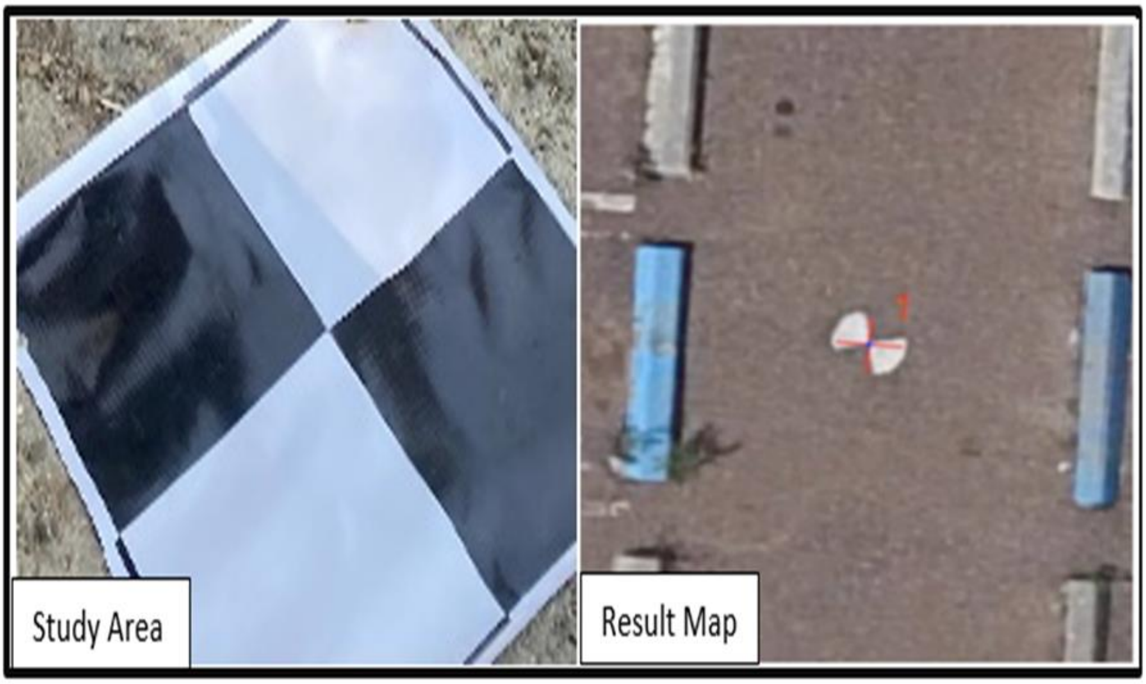

***Figure 5**: Targets Used to Mark Ground Control Points*

***Table 1**: Ground control point coordinates (X, Y,)*

Gcp Number	X (Easting)	Y (Northing)
Gcp1	441808.819	3681655.36
Gcp2	441654.87	3681689.311
Gcp3	442139.944	3682036.232
Gcp4	442035.151	3681701.323
Gcp5	442322.876	3681913.495
Gcp6	441671.11	3682017.972
Gcp7	441975.428	3682009.446

5.1.2 Aerial Image Acquisition Using Drone

The field surveys conducted for obtaining aerial photographs involved the utilization of a DJI Phantom 4 drone. These surveys took place over a span of two days, specifically on

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March 18-19, 2023, during the time frame of 8:00 am to 1:00 pm. The decision to employ the Phantom Four drone stemmed from its affordability, presenting a cost-effective alternative to aerial platforms equipped with expensive apparatus. The drone has a maximum resolution of 4000 x 3000 pixels. This drone has a focal length of 20mm and a fixed aperture size at f/2.8, with a fixed focus range, Figure (6) shows the components of the drone. the device is equipped with advanced collision avoidance technology, further enhancing its functionality and safety. The technical specifications of this aircraft are clearly shown in Table No. (2).

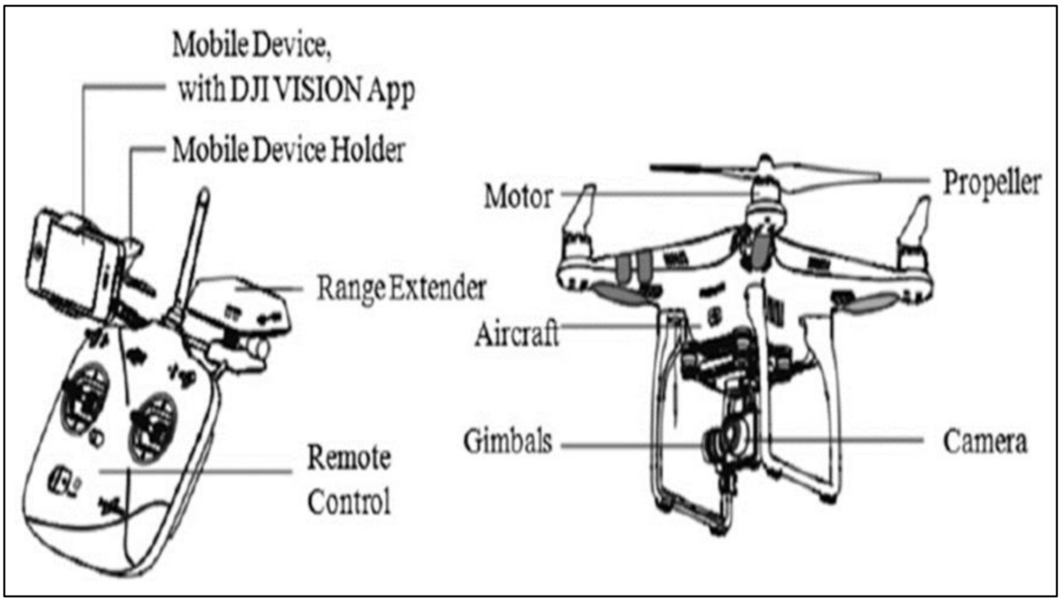

Figure 6: *Phantom Four Drone components*

Table 2: *Specifications of Phantom 4 Drone*

Feature	Specification
Dimensions	Diagonal Size: 350 mm (13.8 inches)
Weight	1380 g (3.06 lbs)
Maximum Flight Time	Up to 28 minutes
Maximum Speed	72 km/h (44.7 mph)
Maximum Altitude	500m
Gps	Built-in GPS and GLONASS positioning systems
Camera	1-inch 20MP CMOS sensor with 4K video capabilities
Battery	Intelligent Flight Battery with 5870mAh capacity and advanced battery management system
Gimbal	3-axis motorized gimbal for smooth camera stability
Operating Range	Up to 7 km
Remote Controller	Integrated 5.5-inch 1080p display with a live video feed and advanced flight controls

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5.1.2.1 Flight Planning

Before utilizing the drone for aerial photography of the designated study area, a meticulous flight plan was devised to ensure adequate coverage and minimize the possibility of data loss, thereby ensuring precise map generation. The flight plan was designed employing the [pix4Dcapture] software as depicted in Figure (7).

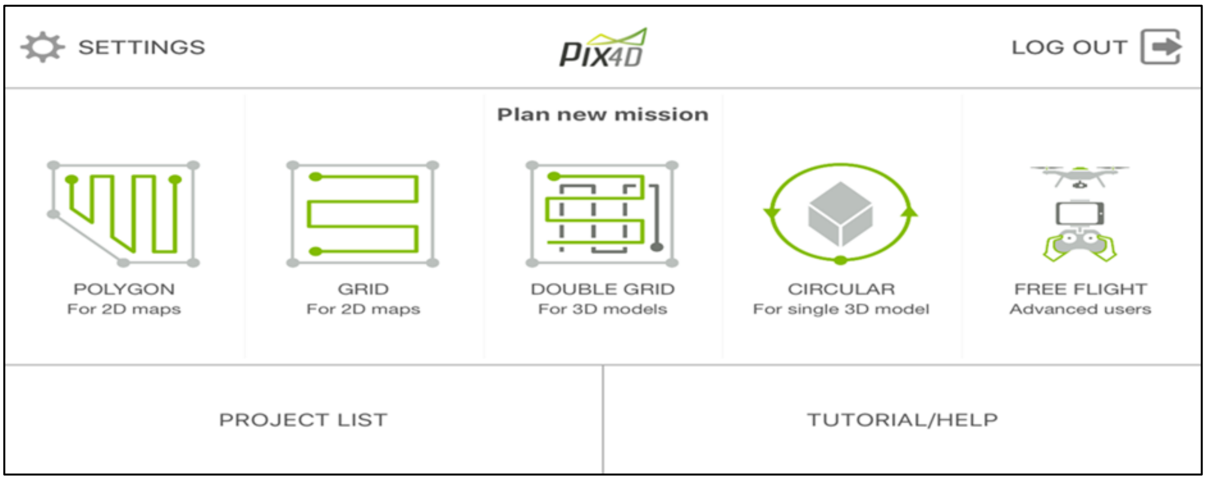

Figure 7: *Flight Line Grid*

In order to guarantee an adequate level of accuracy and prevent data loss, the flight altitude of 55 meters above ground level was selected. The degree of overlap between images was established at 80% in both horizontal and vertical directions, which ensured the achievement of adequate image coverage necessary for precise mapping purposes.

Figure 8*:User Interface Software*

5.2 Aerial Image Processing and Map Creation

After the data was collected, the images were processed using the [Pix4Dmapper] program to create a detailed 2D ortho map of the mapped area (Hsu & Chang, 2015). The following steps were taken to generate the map.

1. Uploading Image for pix4D : Pictures taken during the drone flight were uploaded to Pix4Dmapper, the total number of images was 1800. Set the coordinate reference of the images used (WGS 1984 UTM ZONE 38 N) Because the images contain coordinates, the program automatically detects the coordinates of the images and starts the initial processing.

2. Add (GCPs)and Image Alignment : The process of adding ground control points includes the second process, after uploading the images to the program, the control points have been added to the project as shown in Figure (9). Then start the process of aligning the images and determining the direction. The images are aligned through the common key points between the images, such as angles and clear targets in the images Figure (10), so the common features of each image are identified and aligned with each other.

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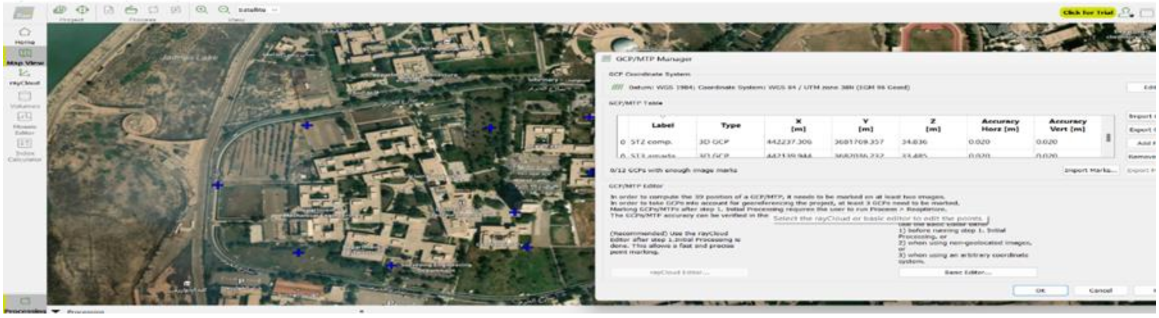

Figure 9: *Adding Ground Control Points to the Study Area*

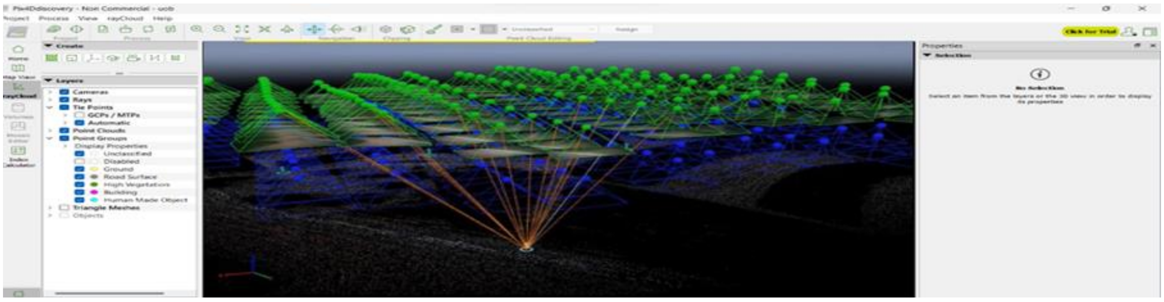

Figure 10*:Data Alignment and Direction Determination with Key Point*

3. Ortho map Creation: At this point, the images are processed and the Ortho map is built. This mosaic acts as a final composite image of the area, which is subject to spatial correction and volume clarity. Figure)11) shows the processing steps and map construction. The accuracy of the mosaic depends on the accuracy of the scenes captured by the drone. In addition, DSM and DTM layers are generated for the area, which contributes to the overall mapping process. Finally, the resulting map is exported in the "TIFF" format, which has high spatial resolution and accurate scale.

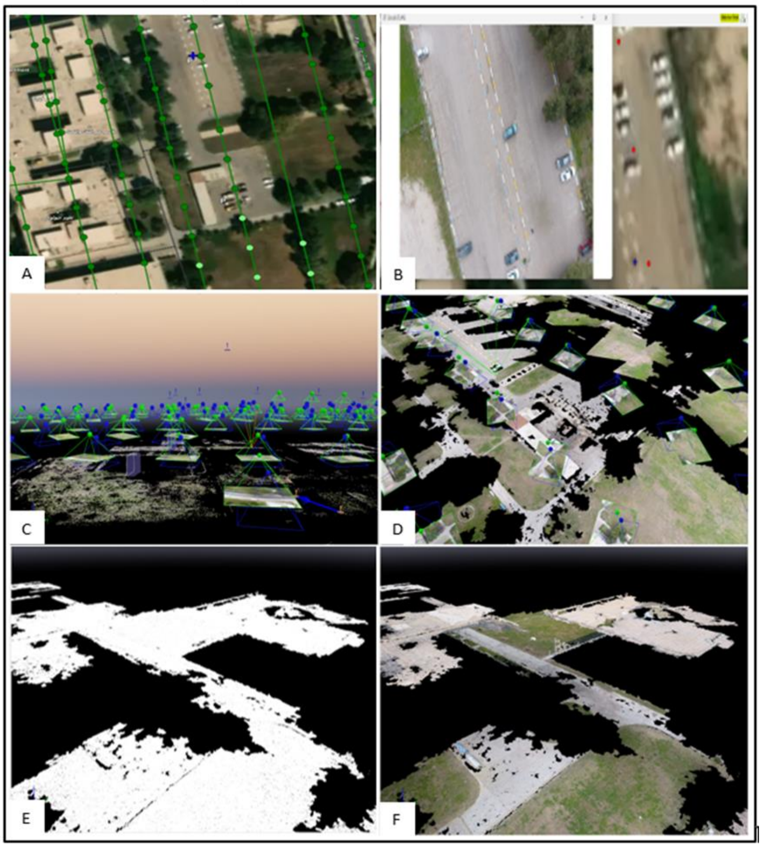

Figure 11: *Processing Steps and Map Construction*

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6. DATASET

In this study, we generated a dataset for the aerial image. The dataset included two parts, the images, and the mask. Table (3) shows the dataset specifications.

Table 3 :*Dataset Specifications*

Dataset	Image Size (Pixel)	Number	Bit Depth
Image	128x128	70591	16
Mask	128x128	70591	8

To prepare the dataset for the aerial image, we used ArcGIS Pro to generate the training data. Polygons around several trees were drawn in the aerial image using visual interpretation techniques. Polygons were used to extract patches from the image that contain trees. To extract the corrections, we used the Export Training Data for Deep Learning tool in ArcGIS Pro. Each patch was 128 x 128 pixels in size with a step of 64 pixels in both the x and y directions. This ensures that each tree is appropriately represented in the dataset and provides enough samples to train the machine learning algorithms. Non-tree spots were randomly selected from regions of the image where trees were not present.

7. YOLO V3

YOLOv3 is an advanced version compared to the previous versions. With the improvements in this version of being able to detect two objects and determine their category in the case when the object is close to each other. Where this is difficult and not possible in previous versions. This version is based on a different architecture consisting of a set of components that work together for accurate object detection. The backbone in this release uses YOLOv3 Darknet-53 convolutional neural network, which consists of 53 layers, this backbone has 4 remaining modules each consisting of s x s convolutional layers as shown in Figure (12) (Redmon & Farhadi, 2018). A ReLU activation function is used between these layers. In this version, feature pyramid network (FPN) technology is also used (Chen, Hsieh, Gochoo, Wang, & Liao, 2019) . Its principle is based on discovering the details of the object at different levels in a way that helps to overcome the problem of inconsistencies in the level of semantic information on the details to be revealed, for example, if the purpose of using the algorithm is to detect bushes or buildings, there are different heights and sizes and differences in the details of the targets. The use of this technology helps with a higher level of target detection and higher accuracy in positioning, as shown in Figure (13). In addition, the version of YOLO V3 uses non-maximal suppression (NMS) (Liu, Nouaze, Mbouembe, & Kim, 2020), the benefit of which is to remove redundant detections as shown In figure (14). Preserving the most accurate box detections in detecting the target in a way that can be used by reducing the repetition process during detection. All these factors make the structure of the YOLOV3 algorithm a unique tool for detecting targets of different sizes and a variety

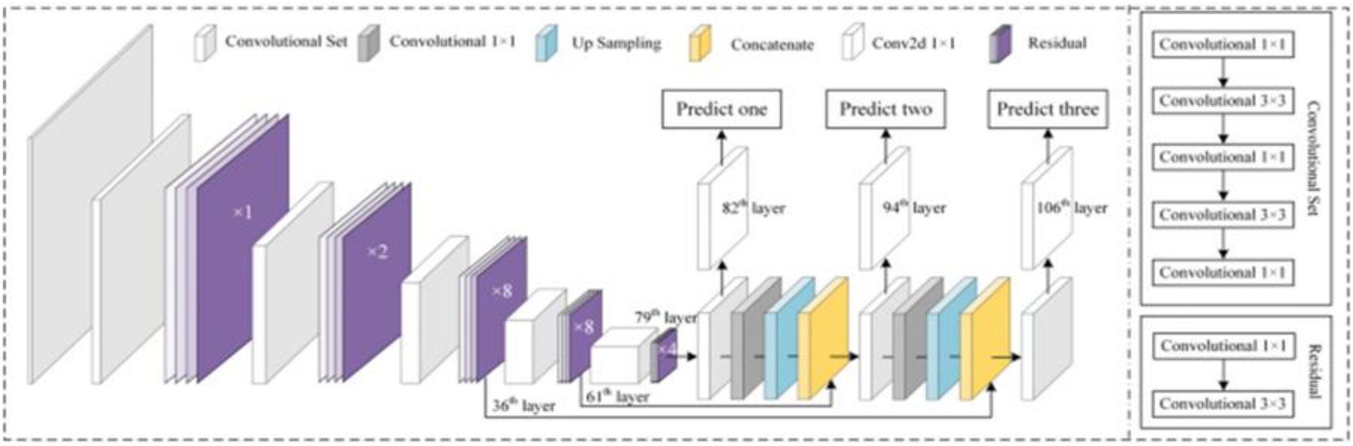

Figure 12*:The Architecture Network for YOLOv3*

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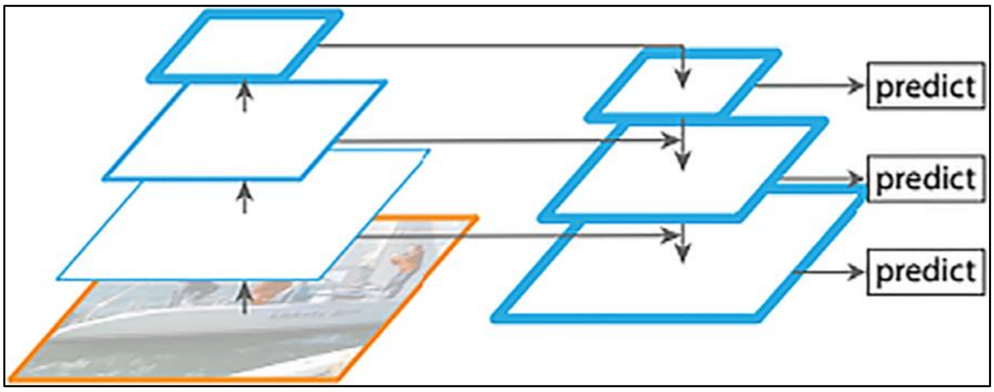

Figure 13*:The Feature Pyramid Network for Yolo V3*

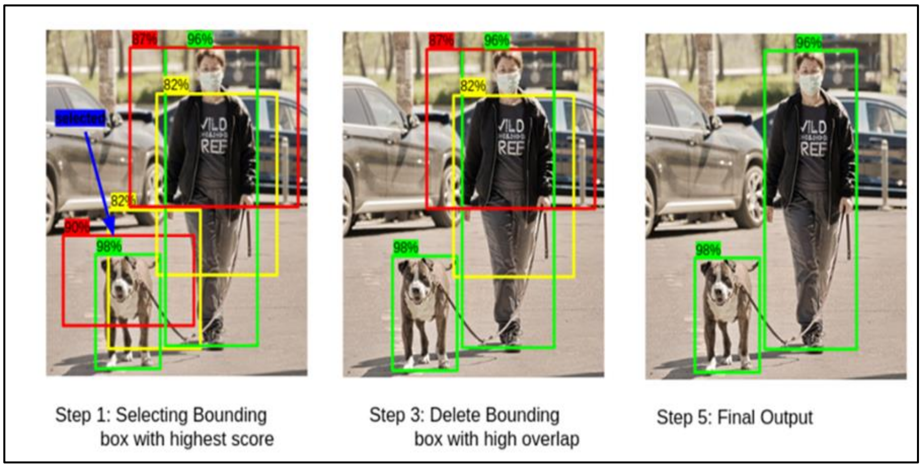

Figure 14: *Non-maximal Suppression in Yolo V3*

7.1 Tree Detection Using AI

Tree detection was carried out on drone images as shown in Figure (15), using the You Only Look Once (YOLO) v3 object detection algorithm. To do this, a specialized training dataset was prepared for each type of image to facilitate the accurate identification of trees within images. YOLO is an object detection algorithm that uses convolutional neural networks (CNNs) to predict the bounding boxes and class probabilities of objects within an image in one shot. YOLO is designed to optimize speed and accuracy, making it a popular choice for object detection tasks in remote sensing applications. The algorithm was implemented in ArcGIS Pro, which allowed for efficient processing and analysis of the image data.

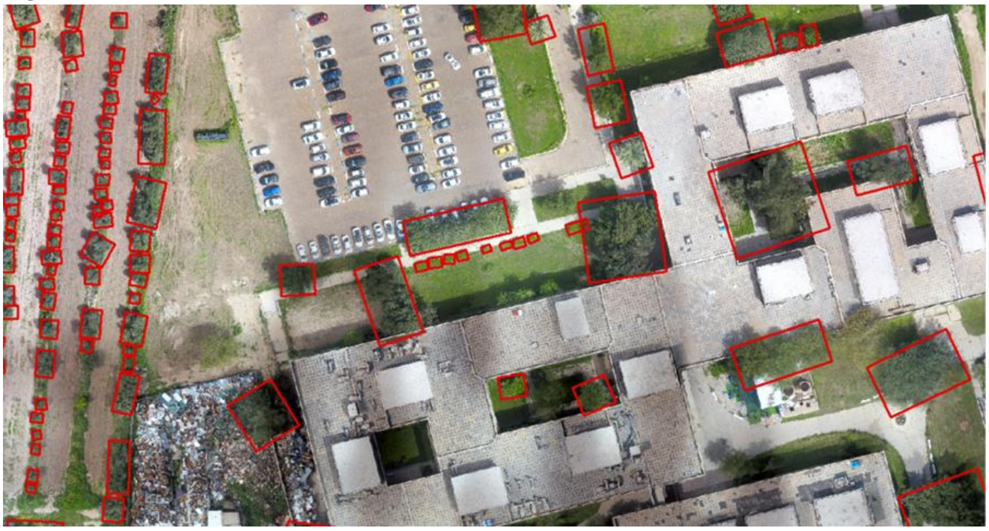

Figure15*:Tree detection using (YOLO) v3*

8. ACCURACY ASSESSMENTS

To evaluate the accuracy of the resulting map and the results of tree detection and vegetation classification. Different evaluation methods were used depending on the methodology of the study. This section will explain these methods

8.1 Root Mean Square (RMSE)

Root Mean Square Error (RMSE). It is a widely used statistical measure for the accuracy of the results of the resulting model by comparing them with specific and known reference data. The RMSE can be calculated using the following equation (Liu, Zheng, Gang, Zhang, & Zuo, 2018):

$$\mathrm{RMSE_X} = \sqrt{\frac{\sum_{I=1}^{N}[(\mathrm{XOi} - \mathrm{XGCPi})^2]}{n}} \quad (1)$$

$$\mathrm{RMSE_Y} = \sqrt{\frac{\sum_{I=1}^{N}[(\mathrm{YOi} - \mathrm{YGCPi})^2]}{n}} \quad (2)$$

$$\mathrm{RMSE_{XY}} = \sqrt{\frac{\sum_{I=1}^{N}[(\mathrm{XOi} - \mathrm{XGCPi})^2]+\sum_{I=1}^{N}[(\mathrm{YOi} - \mathrm{YGCPi})^2]}{n}} \quad (3)$$

Where Yoi and XoiRepresents the GCP data value in the field. YGcpi and XGcpi, The coordinate value obtained from Pix4Dmapper, and N represent the number of points.

8.2 Sorensen Dice Coefficient

Also known as F1 score or Dice similarity. It represents a measure of the similarity or overlap between the output results and the basic fact. It can be represented as shown in the following equation (Al-Dabbagh & Ilyas, 2023):

$$SDC = \frac{2TP}{2\,TP + FP + FP} \quad (4)$$

Where FP represents false positive, FN is false negative, and TP represents true positive.

8.3 Jaccard Index

Jaccard Index, also known as Intersection over Union (IoU). It is a metric used to measure the overlap or similarity between output results and ground fact data. It is widely used in object detection and image segmentation. The following equation shows the metric Jaccard Index (Szpakowski & Jensen, 2019):

$$IoU = \frac{TP}{(TP + FP + FN)} \quad (5)$$

8.4 Dice Loss

It is a loss function that is commonly used in various tasks such as target detection and image segmentation. It was derived from the Sorensen-Dice-Coefficient (SDC), which is used to measure the amount of similarity between two groups of samples. It can be referred to by the following equation (Sudre, Li, Vercauteren, Ourselin, & Cardoso, 2017):

$$Dice\ Loos = \frac{2\sum_i^N p_i g_i}{\sum_i^N p_i^2 + \sum_i^N g_i^2} = \frac{2\hat{\imath}}{i} \quad (6)$$

where i and ^i are the corresponding ground truth mask and predicted mask.

9. RESULTS AND DISCUSSION

9.1 Ortho map Construction

Using the processed data, an orthologous map of the study area was created. The resulting map showed a high level of detail and accuracy, with a spatial resolution of 2 cm and Root Main Square for X-axis 0.00494942m, Y-axis 0.016277724m, and Rmse (x,y) 0.017013556m. To ensure geographical accuracy, the map underwent correction based on the designated geographical reference (WGS 84 / UTM zone 38N), taking advantage of the coordinates associated with the captured images and ground control points of the study area. the Orthotics underwent automatic spatial correction and alignment with the specified geo-reference. By merging a set of images into a seamless mosaic, the ortho map clearly depicted the vegetation, buildings, and other noteworthy features within the study area. This form of mapping resulted in a comprehensive visual overview, making it easier to analyze, interpret and study the captured data, as shown visually in Figure (16).

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Figure 16: *Ortho map of the Study Area*

9.2 Detection Using Yolo v3

In our study, we employed the YOLO v3 deep learning tool for tree detection. a total of 70,591 images were allocated for training, 14,118 images for validation, and 56,472 images for testing. During the training process, the algorithm underwent 40 training iterations, where the data was meticulously analyzed and monitored for loss. The network was trained in 16 batches, ensuring the attainment of convergence results. An initial learning rate of 1e-4 was set for efficient training. To prevent overfitting, an early stopping mechanism was implemented, whereby the training process would halt if the validation loss exceeded a certain threshold. Specifically, if the validation loss did not improve by 0.4 after three epochs, the learning rate was reduced.

Table (4) offers a comprehensive overview of the outcomes obtained from employing the Deep Learning YOLO V3 tool for tree detection in an aerial image dataset.

Table 4*: Aerial Image Result Using Yolo v3 Model*

Assessment Metric	**Dice Loss**	**SDC**	**Jaccard Index**
Value	0.023	0.984	0.943

Figure (17) illustrates the iterative progression curve of the Dice Loss function, serving as a visual representation of the network's convergence and improvement during the training process of the aerial image dataset. The curve showcases the notable enhancements in tree detection performance achieved as the network undergoes successive training iterations with the provided dataset. The figure visually conveys the significant improvements in accuracy and effectiveness in detecting trees within the utilized aerial Image dataset.

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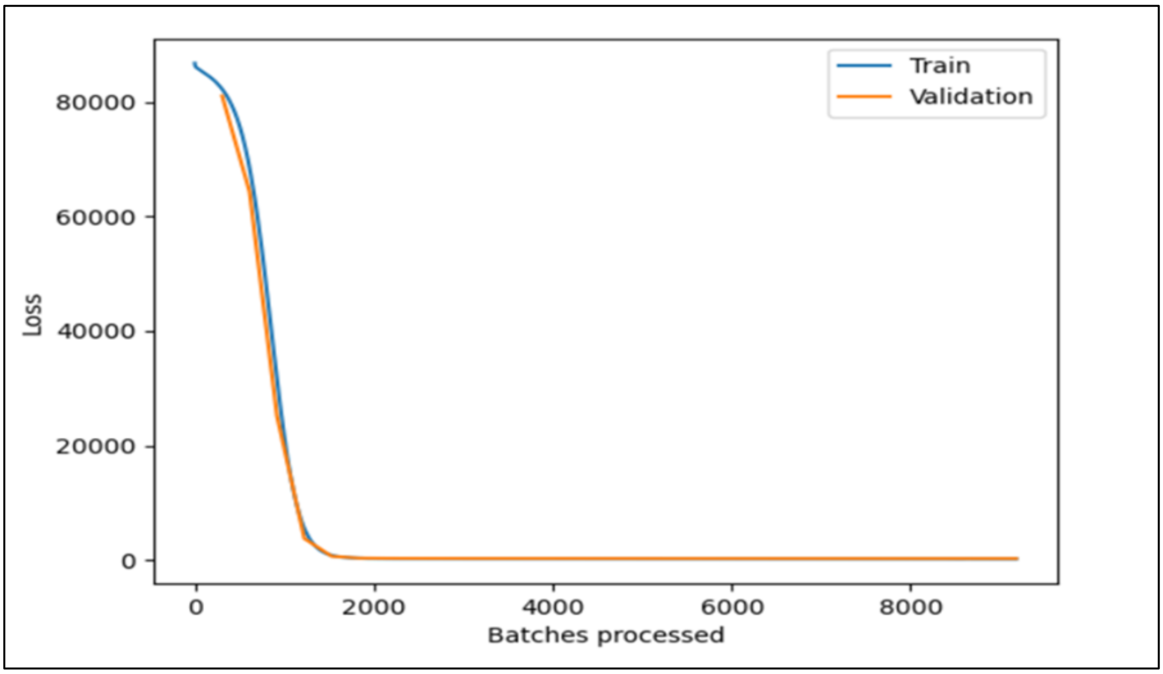

Figure 17: *Dice Loss Function for Aerial Image Dataset*

Figure 18: *Visual Comparison between Ground Truth and YOLO Tree Detection*

The outcomes derived from the generated map demonstrate the efficacy of employing unmanned aerial vehicles (UAVs), specifically drones, for the representation of such maps. This utilization yielded highly precise results, enabling the acquisition of valuable insights into the diverse characteristics present within the designated region. The adoption of the unmanned aerial vehicle approach effectively captured intricate details, thereby facilitating the integration of this data with artificial intelligence methodologies. Consequently, the combination of the UAV-derived information with artificial intelligence techniques facilitated the accurate detection of trees within the area of interest. This amalgamation proved instrumental in streamlining decision-making processes and enabling meticulous analysis of

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vegetation cover. The findings indicate that employing artificial intelligence methods in conjunction with aerial image data exhibited a commendable level of accuracy.

10. CONCLUSION

The research presented in this study explored the feasibility of utilizing high-resolution drone data for the construction of ortho-maps, coupled with the implementation of YOLOV3, an artificial intelligence technique, to identify trees within a specific area of interest. The findings of this study affirm the drone's potential as a robust and efficient tool for representing agricultural maps. Moreover, drones offer the advantage of being a cost-effective platform capable of providing real-time data with high spatial accuracy. The artificial intelligence model exhibited remarkable proficiency in detecting trees within the region, underscoring the potential of integrating these tools with drone platforms to enable rapid and effective identification and analysis of agricultural fields and trees. These outcomes hold significant implications for future studies and projects, particularly those pertaining to the agricultural domain, as they highlight the potential benefits that can be derived from employing such tools.

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