LARGE-SCALE DETECTION, MAPPING, AND INITIAL HEALTH ASSESSMENT OF DATE PALM TREES USING MULTIPLATFORM REMOTELY-SENSED DATA AND DEEP LEARNING TECHNIQUES

By

MOHAMED BARAKAT ABDELFATAH GIBRIL

Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia, in Fulfilment of the Requirements for the Degree of Doctor of Philosophy

December 2023

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DEDICATION

In loving memory of my beloved mother, Nafisa Ali Al-Shaikh, for the love, unwavering support, and endless sacrifices that paved the path for my success

Abstract of thesis presented to the Senate of Universiti Putra Malaysia in fulfilment of the requirement for the degree of Doctor of Philosophy

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Chairman : Associate Professor Helmi Zulhaidi bin Mohd Shafri, PhD
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Reliable and efficient large-scale detection and mapping of date palm plantations through multiplatform remote sensing are crucial to developing palm tree inventories and sustainable management of the date palm industry. Given the increasing availability of unmanned aerial vehicle (UAV) images with limited spectral information, the high intraclass variance of palm trees, the variations in spatial resolutions of data, and the complexity of image contexts, accurate and automatic large-scale mapping of date palm trees from multisource and multidate data remains a challenge.

Recent studies on date palms using convolutional neural network (CNN)-based object detection methods have primarily focused on limited study sites and relied on a single data source. In-depth investigations on the generalizability and transferability of semantic and instance segmentation models for mapping date palm trees from multiplatform remotely sensed data are lacking. Moreover, no effort has been exerted to assess the feasibility of evaluating the health of date palm trees from large-scale UAV-based images.

This study aims to provide an end-to-end, efficient, and transferable deep learning architecture for the large-scale mapping of date palm trees and initial health assessment from UAV-based images. Considering the ability of deep vision transformers to capture robust local–global feature representations, this research hypothesizes that transformer-based models can deliver effective outcomes for large-scale mapping and assessment of date palm trees. This thesis evaluates various deep vision transformers and presents an efficient and cost-effective transformer-based framework to identify, quantify, monitor, and evaluate the overall well-being of palm trees using large-scale multiplatform images. This framework integrates a mask region CNN, a hierarchical Swin transformer, a feature pyramid network, and slicing-aided hyperinference to efficiently undertake large-scale instance segmentation of individual date palm trees, subsequently converting the results into a vector representation.

Experimental results show that the examined deep vision transformers for the semantic segmentation of date palm trees are comparable to several CNN-based models and achieve satisfactory results in mapping date palm trees from UAV images. The SegFormer model, followed by the UperNet-Swin transformer, outperforms all the evaluated CNN-based models in the multiscale testing dataset and the additional unseen UAV test dataset. Moreover, the SegFormer model can be fine-tuned to delineate date palm trees using VHR WorldView-3 satellite imagery.

The performance of the proposed instance segmentation framework surpasses that of several CNN-based models, demonstrating effective detection and delineation of individual date palm trees with F-scores of 94% and 93%, respectively. The proposed framework also exhibits great generalizability in detecting and mapping individual date palm trees from different UAV images with diverse spatial resolutions. The transformer-based architecture is fine-tuned through transfer learning to differentiate between healthy and unhealthy date palm trees. The potential generic condition of date palm trees is predicted with mAP_{50} of 80.2%.

In sum, the proposed framework provides an efficient tool for accurately detecting and mapping individual date palm trees from multiscale and multidate UAV images, thereby building and updating geospatial databases and enabling consistent monitoring of date palm trees. It is suitable for individual tree crown delineations and other Earth-related applications.

Keywords: UAV, Mapping, Date Palm Trees, Deep Learning, Computer Vision, Vision Transformers, Tree Crown Detection, Tree Health Assessment.

SDG : Zero Hunger, Responsible Consumption and Production, Life on Land, Sustainable Cities and Communities

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Doktor Falsafah

PENGESANAN BERSKALA BESAR, PEMETAAN, DAN PENILAIAN KESIHATAN AWAL POKOK KURMA MENGGUNAKAN DATA PENDERIAAN JAUH PELBAGAI PLATFORM DAN TEKNIK PEMBELAJARAN MENDALAM

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Pengesanan dan pemetaan ladang pokok kurma berskala besar yang boleh dipercayai dan efisien melalui penderiaan jauh pelbagai platform adalah penting untuk membangunkan inventori pokok kurma, dan pengurusan lestari industri pokok kurma. Dengan peningkatan ketersediaan imej pesawat tanpa pemandu (UAV) yang mempunyai maklumat spektral yang terhad, varians intrakelas pokok kurma yang tinggi, variasi dalam resolusi spatial data, dan kompleksiti konteks imej, pemetaan berskala besar yang tepat dan automatik dari data pelbagai sumber dan pelbagai tarikh tetap menjadi cabaran.

Kajian terbaharu ke atas pokok kurma menggunakan kaedah pengesanan objek berasaskan rangkaian neural konvolusionl (CNN) memberi tumpuan terutamanya pada tapak kajian yang terhad dan bergantung kepada sumber data tunggal. Penelitian mendalam ke atas kebolehgeneralisasian dan kebolehalihan model segmentasi semantik dan instans untuk pemetaan pokok kurma daripada data penderiaan jauh pelbagai platform adalah kurang. Tambahan pula, tiada usaha yang telah dijalankan untuk menilai kesihatan pokok kurma dari imej UAV berskala besar.

Kajian ini bertujuan untuk mengutarakan seni bina pembelajaran mendalam yang efisien dan boleh dipindahkan untuk pemetaan pokok kurma berskala besar serta penilaian kesihatan awal dari imej UAV. Memandangkan kemampuan transformer visi mendalam untuk menangkap representasi ciri lokal-global yang kukuh, kajian ini menghipotesiskan bahawa model berasaskan transformer berupaya untuk mengutarakan hasil yang efektif bagi penilaian dan pemetaan pokok kurma. Tesis in menilai pelbagai transformer visi dan

mengutarakan kerangka berasaskan transformer yang efisien dan kos efektif bagi mengenal pasti, menyatakan kuantiti, memantau dan menilai kesejahteraan pokok kurma menggunakan imej pelbagai platform berskala besar. Kerangka ini mengintegrasikan kawasan topeng CNN, transformer Swin berhierarki, rangkaian piramid berciri, dan penghirisan bantuan hiperinferens untuk menjalani segmentasi instans pokok kurma secara individu dengan efisien, seterusnya menukar hasil kepada representasi vektor.

Hasil eksperimen menunjukkan bahawa transformer visi mendalam untuk segmentasi semantik pokok kurma adalah setanding dengan beberapa model berasaskan CNN dan memperoleh hasil yang memuaskan dalam pemetaan pokok kurma dari imej UAV. Model SegFormer, diikuti oleh transformer UperNet-Swin, mengatasi semua model berasaskan CNN dalam set data pengujian pelbagai skala dan set data UAV tambahan yang tidak kelihatan. Selain itu, model SegFormer boleh diperhalusi bagi menggambarkan pokok kurma menggunakan imejan satelit VHR WorldView-3.

Prestasi kerangka segmentasi instans yang disyorkan yang melepasi beberapa model berasaskan CNN, menunjukkan pengesanan dan penggambaran yang efektif bagi pokok kurma individu dengan skor F masing-masing sebanyak 94% dan 93%. Kerangka yang disyorkan juga menunjukkan kebolehgeneralisasian yang hebat dalam mengesan dan memetakan pokok kurma individu dari imej UAV dengan resolusi spatial yang pelbagai. Seni bina berasaskan transformer diperhalusi melalui pembelajaran pemindahan untuk membezakan antara pokok kurma yang sihat dan yang tidak sihat, terutamanya yang mempunyai serangan yang teruk, dengan mAP_{50} sebanyak 80.2%.

Ringkasnya, kerangka yang disyor menyediakan alat yang efisien untuk pengesanan dan pemetaan yang tepat bagi pokok kurma individu dari imej UAV pelbagai skala dan pelbagai tarikh, membangun dan mengemaskinikan pangkalan data geospatial serta membolehkan pemantauan pokok kurma yang konsisten. Ia juga sesuai untuk penggarisan silara pokok individu dan aplikasi berkaitan Bumi yang lain.

Kata Kunci: UAV, Pemetaan, Pokok Kurma, Pembelajaran Mendalam, Komputer Visi, Visi Transformer, Pengesanan Mahkota Pokok, Penilaian Kesihatan Pokok.

SDG : Kelaparan Sifar, Penggunaan & Pengeluaran Bertanggungjawab, Kehidupan di Darat, Bandar dan Masyarakat Mampan.

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LIST OF ABBREVIATIONS

ASPP	Atrous Spatial Pyramid Pooling
CNN	Convolutional Neural Network
COCO	Common Objects in Context
CV	Computer Vision
DANet	Dual Attention Network
DCNN	Deep Convolutional Neural Network
DL	Deep Learning
DPT	Dense Prediction Transformer
FC	Fully Connected
FCN	Fully Convolutional Network
FFN	Feed-forward Network
FLOPs	Floating-Point Operations
FPN	Feature Pyramid Network
FPS	Frames Per Second
GDAL	Geospatial Data Abstraction Library
GEOBIA	Geographic Object-Based Image Analysis
GNSS	Global Navigation Satellite System
GSD	Ground Space Distance
GT	Ground-truth
ITC	Individual Tree Crown
JSON	JavaScript Object Notation
KML	Keyhole Markup Language
LN	LayerNorm
Mask R-CNN	Mask Region Convolutional Neural Network
ML	Machine Learning

MLPs	Multi-layer Perceptrons
MiT	Mix Transformer
PEs	Position Encodings
PointRend	Point-based Rendering
PPM	Pyramid Pooling Module
PSPNet	Pyramid Scene Parsing Network
R-CNN	Region-based Convolutional Neural Networks
RGB	Red-Green-Blue
RINEX	Receiver Independent Exchange Format
ROIs	Regions of Interests
RTK/PPK	Real-time Kinematic/Postprocessed Kinematic
ResNets	Residual Learning Networks
SAHI	Slicing Aided Hyper Inference
SODA	Sensor Optimized for Drone Applications
SRTM	Shuttle Radar Topography Mission
Swin	Shifted Window Transformer
UAV	Unmanned Aerial Vehicle
UperNet	Unified Perceptual Parsing Network
UTM	Universal Transverse Mercator
VHSR	Very-High Spatial Resolution
ViT	Vision Transformer
VRT	Virtual GDAL Dataset
W-MSA	Window Multi-head Self-attention
WGS84	World Geodetic System 84
WV-3	WorldView-3
YOLACT	You Only Look At CoefficientTs
UTM	Universal Transverse Mercator

VHSR	Very-High Spatial Resolution
ViT	Vision Transformer
W-MSA	Window Multi-head Self-attention
WGS84	World Geodetic System 84
WV-3	WorldView-3
YOLACT	You Only Look At CoefficientTs

CHAPTER 1

INTRODUCTION

1.1 Background

Date palm trees (*Phoenix dactylifera L.*), which are an arborescent monocotyledonous tree species, are one of the oldest perennial fruit trees (Riad, 1996) and have been one of the most cultivated fruit trees since the Neolithic/Early Bronze Age (Tengberg, 2012). Date palm trees can generally be grown in arid and semiarid environments; are planted extensively on the Arabian Peninsula, in West Asia, and in North Africa; and have successfully been domesticated and spread to other areas with a suitable climate and sufficient water resources (Krueger, 2021). Moreover, date palm trees are resilient, can survive in tremendously harsh climates, tolerate saline conditions and alkaline soils, and may live for over a century (Chao & Krueger, 2007; Kurup, Hedar, Al Dhaheri et al., 2009). These trees play a considerable role in harsh arid and semiarid environments because they act as windbreaks, preventing desertification and preserving and stabilizing arid and semiarid environments (Kurup, Hedar, Dhaheri, et al., 2009).

Date palm is an economically valuable fruit species with cultural, symbolic, and spiritual importance in Middle Eastern and North African countries (Al-Khayri et al., 2018). According to the Food and Agriculture Organization (FAO, 2023), the world production of dates has increased from 1,852,592 tons in 1961 to 9,656,378 tons in 2021. The world's total harvested area increased over six times from 1961 (240,972 ha) to 2021 (1,301,979 ha). Given the socioeconomic importance of date palm trees, date production must be monitored, preserved, and precisely managed. However, estimating the population of palm trees and the harvest are derived on the basis of the total quantity of the produced dates, and accurate quantification of date palm trees is either limited or obsolete (María Culman et al., 2020). Precise information about the number, distribution, and health of date palm trees is crucial for sustainable management, disease and pest control, and yield estimation.

Continuous large-scale date palm tree mapping and monitoring using traditional field-based techniques can be challenging given the enormous number of trees that are distributed over vast agricultural and urban areas. Remote sensing technologies offer valuable and feasible tools for acquiring and observing large areas with comprehensive options for resolution (Malatesta et al., 2019; Pei et al., 2018; Xie et al., 2008). A tremendous amount of satellite-based data is being collected and has been used extensively for the extraction of vegetation cover, forestry, and changes over Earth's surface at regional and global scales (Disney, 2016; Gärtner et al., 2014; Hilker et al., 2015; Kumagai, 2011; Marston et al., 2017; Spiekermann et al., 2015; A. Zhao et al., 2019). However, satellite and piloted aircraft are constrained by their ability to deliver adequate spatial and temporal resolutions, which are essential to several applications that require very high spatial resolution (VHSR) and short revisit times (Nebiker et al., 2008; Senthilnath et al., 2017).

The advent of cost-effective unmanned aerial vehicle (UAV) platforms and the miniaturization of sensing technologies (i.e., red–green–blue, multispectral, hyperspectral, thermal, and LIDAR) have considerably contributed to the advancement and success of versatile precision agriculture applications (Gonzalez et al., 2018). The capabilities of UAVs in acquiring images with flexible revisit scheduling at low altitudes with ultraspatial and temporal resolutions have enabled the observation of small individual trees/plants and the extraction of information at a fine scale that can support farmers in their decision-making, improve agricultural production, and optimize the utilization of resources (Candiago et al., 2015; Xiang & Tian, 2011). Coupled with the growing availability of VHSR remotely sensed data, a broad spectrum of machine learning (ML) techniques has been used and developed to support precision agriculture, which can be used to provide meaningful information, such as tree species classification, tree crown delineation, tree counting, and tree health assessment.

Traditional classification techniques based on geographic object-based image analysis (GEOBIA) have extensively been used to map various tree species. Mapping tree species and individual tree crown (ITC) delineation through GEOBIA comprises three main stages, which greatly influence the quality of the results, including image segmentation, selection of relevant features, and ML algorithms. For instance, inappropriate selection of image segmentation parameters may result in under- and oversegmentations of the object of interest, which can degrade classification accuracy (Gibril et al., 2020). Moreover, the values of the shallow features of image objects (i.e., mean of spectral indices, textural, and geometrical attributes) can also notably vary among image datasets, and such variation affects the empirical settings of parameter thresholds (Zhang et al., 2019). Considering the complexity of ITCs (i.e., different tree shapes, sizes, and overlapped crowns) and the dependence of GEOBIA on segmentation parameters and handcrafted features, the generalizability of GEOBIA across different scenes and environments is challenging (Martins et al., 2021).

In recent years, deep learning (DL), as a subfield of ML and artificial intelligence (AI), has received considerable attention in the field of remote sensing and has increasingly been used in ITC detection and mapping. In contrast to the classical ML models, DL is data-driven, thus eliminating the need for the construction of manually handcrafted features of hierarchal data representations; high-level deep features are automatically learned from an input of imagery datasets. Moreover, DL outperforms classical ML techniques by effectively tackling the curse of dimensionality and achieving an improved and consistent level of classification accuracies from massive image datasets without a considerable drop in accuracy (Malambo et al., 2019).

DL models, especially convolutional neural networks (CNNs), have been proven to have excellent performance in extracting tree crowns and mapping tree species from UAV data. Their effectiveness spans a variety of tasks such as patch-based classification (Hartling et al., 2019; Kolanuvada & Ilango, 2021; Pearse et al., 2021), object detection (Liu et al., 2021; Moura et al., 2021; Xia et al., 2021; Zamboni et al., 2021), semantic segmentation (Ji et al., 2022; Q. Sun et al., 2022; Veras et al., 2022) and instance segmentation (Lassalle et al., 2022; Y. Li et al., 2022; Mingxia Yang et al., 2022). CNNs automatically learn high-level deep features and complex patterns from input imagery datasets through learnable layered convolutions.

The extraction of feature maps using traditional CNN-based models is conducted using convolutional operations within a localized region (local receptive fields). However, the inherent localized focus in CNNs poses challenges in effectively capturing explicit long-range relationships and contextual information. Various techniques have integrated self-attention mechanisms into CNNs to address this limitation and capture global information. Some of these techniques include the pyramid pooling module (Xiao et al., 2018), object context block (Yuan et al., 2020), crisscross attention block (Zilong Huang et al., 2019), and dual attention module (Fu et al., 2019). These techniques aggregate global data by combining the locally extracted feature maps instead of explicitly encoding the global context (Mou et al., 2020). Therefore, extracting holistic global context from remotely sensed data with intricate backgrounds using CNNs remains difficult.

The outstanding achievements of transformers (Vaswani et al., 2017) in natural language processing (NLP) have paved the way for exploring novel research directions in computer vision (CV). These advancements have resulted in remarkable developments and notable performance enhancements. In contrast to CNNs, transformers have larger receptive fields, and the operations within transformers are parallelizable and independent of order, enabling vision transformers to effectively capture global contextual information through self-attention mechanisms and achieve a higher level of representational capability (Xia et al., 2022; Zhou et al., 2022). In recent years, remote sensing research has witnessed an increasing focus on investigating the possibility of using various vision transformers for tasks involving image classification (Jamali et al., 2022; Jamali & Mahdianpari, 2022), semantic segmentation (Abozeid et al., 2022; Chen et al., 2022; Gao et al., 2021; Panboonyuen et al., 2021; Yang et al., 2022), object detection (Chen & Shang, 2022; Mekhalfi et al., 2022), and instance segmentation (Fan et al., 2022).

1.2 Problem Statement

Reliable and efficient mapping of date palm trees from remotely sensed data is crucial for developing palm tree inventories, continuous monitoring, vulnerability assessments, environmental control, and long-term management. Given the increasing availability of different VHSR images (i.e., multiplatform aerial images) with limited spectral information (i.e., RGB) and the variations in spatial resolutions of data (ranging from a few centimeters to meters), accurate mapping of date palm trees from VHSR images is challenging. The differences in image contexts and backgrounds (i.e., agricultural projects, small farms, urban landscapes) further contribute to the complexity of this task.

Various studies have attempted to map date palm trees from various sources of remotely sensed data using classical ML (pixel- and object-based methods; Al-Ruzouq et al., 2018; Dahy et al., 2021; Mihi et al., 2019; Mulley et al., 2019; Nezamabadi-pour, 2010; Shareef, 2018). Although these techniques have demonstrated satisfactory results in limited study areas, they are case-specific in nature and heavily rely on the analyst's experience and knowledge. This reliance is necessary to determine the appropriate image segmentation parameters, features, and classifiers, complicating automated processing. Such complexity often leads to considerable variations in the classification results from one case to another and from one person to another. Moreover, achieving satisfactory accuracy on a large scale remains difficult (Li et al., 2019).

Over the past few years, DL algorithms have been extensively utilized across various CV applications related to the detection and mapping of different tree species. However, limited studies have focused on detecting date palm trees using CNN-based object detection models from different aerial images acquired by UAVs (Ammar et al., 2021; Jintasuttisak et al., 2022) and aircraft (Culman et al., 2020a).

While these studies have shown satisfactory detection accuracies in limited study areas, the focus on the automatic large-scale mapping and detection of individual date palm trees from VHSR images using state-of-the-art CNNs and deep vision transformers has been limited. An in-depth investigation of the generalizability and transferability of DL models for detecting and mapping date palm trees from multiscale and multiplatform remotely sensed data is lacking. In addition, no effort has been exerted to assess the potential of evaluating the health of date palm trees from large-scale UAV-based images.

1.3 Research Objectives

The main aim of this study is to provide an end-to-end, efficient, and transferable DL technique for the large-scale mapping and detection of date palm trees from multiscale UAV-based images. The specific objectives of this thesis are as follows:

1. examine the reliability and efficiency of deep CNN and transformer-based models in large-scale mapping of date palm trees from multiplatform aerial and satellite-based images,
2. develop an automatic framework for large-scale mapping and detection of individual date palm trees from multiscale UAV images,

3. assess and verify the generalizability and transferability of the evaluated semantic and instance segmentation models, and
4. explore the feasibility of evaluating the health of date palm trees through the utilization of RGB images obtained by UAVs.

1.4 Research Questions

This thesis attempts to address the following research questions thoroughly:

1. To what degree do deep vision transformers surpass CNNs in the large-scale mapping of date palm trees from multiplatform aerial images?
2. How do transformer-based architectures perform in detecting and mapping individual date palm trees when considering the varying spatial resolution of VHSR data and complexities, such as overlapping palm crowns and diverse surrounding environments?
3. To what extent can DL models developed for detecting and mapping date palm trees from UAV images generalize to different geographical locations?
4. Can DL models be used to assess the health of individual date palm trees on the basis of RGB UAV-based images?

1.5 Significance of Research

Given the substantial commercial, environmental, and cultural value of date palm trees, reliable and efficient detection and mapping of date palm trees are essential for the monitoring, preservation, and sustainable management of the date industry. The significance of this research is rooted in its capacity to advance the field of date palm tree detection and mapping from remotely sensed VHSR data.

The first contribution of this research is the comprehensive assessment of various CNN-based architectures and state-of-the-art deep vision transformers in the large-scale mapping of date palm trees from multi-platform aerial and satellite-based images. An accurate and comprehensive date palm tree labeled dataset was developed from multiscale, multidate VHSR data. This dataset is a valuable resource for developing and evaluating state-of-the-art DL architectures.

Second, this thesis introduces an efficient transformer-based DL framework that considerably improves the efficiency of large-scale mapping and detection of individual date palm trees from VHSR data. A novel data conversion method was developed to convert vector data to the common objects in context (COCO) annotation format. Moreover, the slicing-aided hyper inference (SAHI) technique was improved to efficiently undertake large-scale instance segmentation of individual date palm trees and transform the results to vector format.

Moreover, the generalizability and transferability of the proposed framework amplify its potential impact, enabling its adoption and implementation in mapping and detecting date palm trees in similar geographical regions. Overall, the proposed framework is an efficient tool that enables the automatic development of date palm tree inventories, updating the existing geospatial databases for different studies, and consistently monitoring date palm trees from multiscale UAV-based images. Furthermore, this thesis attempts to evaluate the potential of assessing the health of individual date palm trees from RGB UAV-based images.

Collectively, this research could support decision-making processes for farmers, decision-makers, and policymakers, leading to more effective and sustainable management of the date palm industry. This research has the potential to contribute substantially to various fields, including agriculture, forestry, environmental studies, inventory management, and resource planning.

1.6 Scope of the Study

This research mainly focuses on evaluating the performance, generalizability, and transferability of state-of-the-art semantic segmentation architectures for large-scale date palm tree mapping from multiplatform aerial images. Moreover, it proposes a transformer-based DL framework for individual date palm tree mapping using multiscale UAV-based data, and it ultimately attempts to evaluate the potential of assessing the health of palm trees from RGB images.

Owing to the unavailability of multispectral, hyperspectral, and LIDAR datasets across the study area, this research solely utilizes VHSR RGB images. It only focuses on the generic mapping of date palm trees and does not consider mapping the intraclass variations and the age of palm trees. This research classifies date palm trees as healthy or unhealthy on the basis of visual characteristics, without delving into the underlying causes of palm tree mortality.

1.7 Thesis Organization

This thesis is organized into five chapters, as follows:

Chapter One details and highlights the background of the research topic, the problem statement, the objectives, the research questions, and the study's significance, scope, and limitations.

Chapter Two discusses the characteristics of date palm trees, pests and diseases that attack them, and remote sensing technologies. It reviews ML and DL techniques used in mapping and detecting various tree species, as well as previous studies on date palm tree detection and mapping using DL techniques.

Chapter Three describes the material and the methods used to achieve the objectives of this research. It includes data acquisition, preprocessing and preparation, the design of DL architectures for versatile tasks, experimental settings, and validation procedures.

Chapter Four presents and discusses the main findings of this research, including date palm tree segmentation from multiscale candidate VHSR images, individual date palm tree detection and mapping, and the potential health assessment of date palm trees.

Chapter Five summarizes the key findings derived from this research and presents recommendations for further studies.

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