AI Powered Tree Precision Support System for Detection and Height Measurement

B.Tech-AIML Semester- IV

Prepared at

BISAG-N

ISO 9001:2008
ISO 27001:2013
CMMI LEVEL-5

Bhaskaracharya National Institute for Space Applications & Geo-informatics
Ministry of Electronics and Information Technology, Govt. of India.

Gandhinagar

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SUBMITTED TO

Charotar University of Science and Technology

अमृतं तु विद्या CHARUSAT

Department of Artificial Intelligence and Machine Learning

Chandubhai S Patel Institute of Technology (CSPIT), CHARUSAT.

BISAG-N

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CERTIFICATE

*This is to certify that the project report compiled by **Ms. Kunjalba Vala** student of 4th Semester **B.Tech - AIML from Charotar University of Science and Technology** have completed their Summer internship project satisfactorily. To the best of our knowledge this is an original and bonafide work done by them. They have worked on Web-based application for "**AI Powered Tree Precision Support System for Detection and Height Measurement**", starting from May 16th, 2024 to August 15th, 2024.*

During their tenure at this Institute, they were found to be sincere and meticulous in their work. We appreciate their enthusiasm & dedication towards the work assigned to them.

We wish them every success.

Dr. Yagnesh Vyas
Project Director,
BISAG- N, Gandhinagar

Punit Lalwani
CISO,
BISAG- N, Gandhinagar

CERTIFICATE

*This is to certify that the 4th Semester Internship Project entitled "**AI Powered Tree Precision Support System for Detection and Height Measurement**" has been carried out by* **Ms. Kunjalba Vala** *under my guidance in fulfilment of the degree of Bachelor of Technology in ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING (4th Semester) of Charotar University of Science and Technology during the academic year 2023-2024.*

Guide :

Dr. Nirav Bhatt

HoD AIML,

CHARUSAT.

About BISAG- N

ABOUT THE INSTITUTE

Modern day planning for inclusive development and growth calls for transparent, efficient, effective, responsive and low cost decision making systems involving multi-disciplinary information such that it not only encourages people's participation, ensuring equitable development but also takes into account the sustainability of natural resources. The applications of space technology and Geo–informatics have contributed significantly towards the socio-economic development. Taking cognizance of the need of geo-spatial information for developmental planning and management of resources, the department of Ministry of Electronics and Information Technology, Government of India, established "Bhaskaracharya National Institute for Space Applications and Geo-informatics" (BISAG- N). BISAG- N is an ISO 9001:2008, ISO 27001:2005 and CMMI: 5 certified institute. BISAG- N which was initially set up to carryout space technology applications, has evolved into a centre of excellence, where research and innovations are combined with the requirements of users and thus acts as a value added service provider, a technology developer and as a facilitator for providing direct benefits of space technologies to the grass root level functions/functionaries.

BISAG- N's Enduring Growth

Since its foundation, the Institute has experienced extensive growth in the sphere of Space technology and Geo-informatics. The objective with which BISAG- N was established is manifested in the extent of services it renders to almost all departments of the State. Year after year the institute has been endeavouring to increase its outreach to disseminate the use of geo-informatics up to grassroots level. In this span of nine years, BISAG- N has assumed multi-dimensional roles and achieved several milestones to become an integral part of the development process of the Gujarat State.

BISAG- N Journey

2003-04

Gujarat SATCOM Network

2007-08

Centre for Geo-informatics Applications

2010-11

Academy of Geo-informatics for Sustainable Development

2012-13

A full-fledged Campus

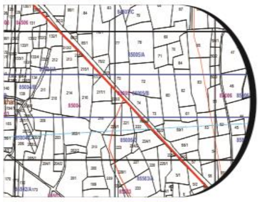
Activities

Satellite Communication..

for promotion and facilitation of the use of broadcast and teleconferencing networks for distant interactive training, education and extension.

Remote Sensing..

for Inventory, Mapping, Developmental planning and Monitoring of natural & man-made resources.

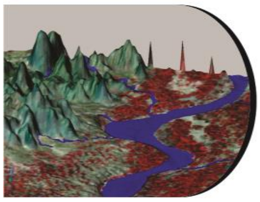


Geographic Information System..

for conceptualization, creation and organization of multi purpose common digital database for sectoral/integrated decision support systems.

Global Navigation Satellite System..

for Location based Services, Geo-referencing, Engineering Applications and Research.



Photogrammetry..

for Creation of Digital Elevation Model, Terrain Characteristic, Resource planning.

Cartography..

for thematic mapping, value added maps.

Software Development..

for wider usage of Geo-spatial applications, Decision Support Systems (desktop as well as web based), ERP solutions.

Education, Research and Training..

for providing Education, Research, Training & Technology Transfer to large number of students, end users & collaborators.

Applications of Geospatial Technology for Good Governance: Institutionalization

Through the geospatial technology, the actual situation on the ground can be accessed. The real life data collected through the technology forms the strong foundation for development of effective social welfare programs benefiting directly the grass root level people. The geospatial data collected by the space borne sensors along with powerful software support through Geographic Information System (GIS), the vital spatio-temporal maps, tables, and various statistics are being generated which feed into Decision Support System (DSS).

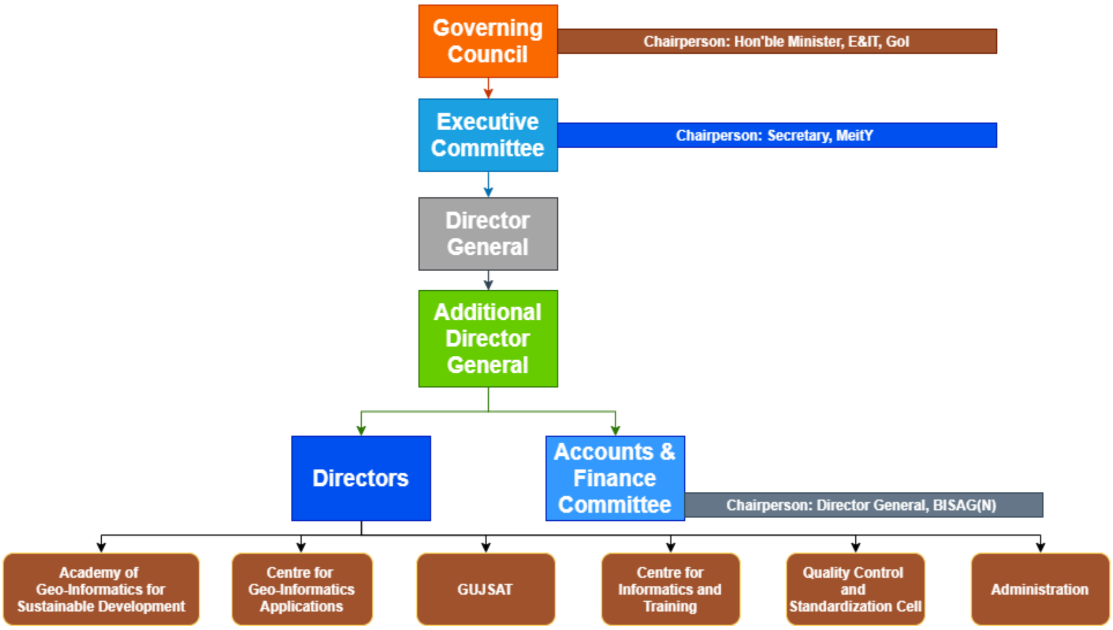
A multi-threaded approach is followed in the process of institutionalization of development of such applications. The 5 common threads which run through all the processes are: *Acceptability, Adaptability, Affordability, Availability and Assimilability*.
These are the "Watch Words" which any application developer has to meet. The "acceptability" addresses the issue that the application developed has met the wide acceptability among the users departments and the ultimate end beneficiary by way of providing all necessary data and statistics required. The "affordability" addresses the issue of the application product being cost effective. The "availability" aspect looks into aspect of easily accessible across any platform, anywhere and anytime. The applications should have inbuilt capability of easy adaptability to the changing spatio- and temporal resolutions of data, new aspects of requirements arising from time to time from users. The assimilability aspect ensures that the data from various sources / resolutions and technologies can be seamlessly integrated.

ACCEPTABILITY	▪ Problem definition by users • Proof of Concept development without financial liability on users ▪ Execution through collaboration under user's ownership
ADOPTABILITY	▪ Applications as per present systems & database ▪ Maximum Automation ▪ Minimum capacity building requirement at the user end
AFFORDABILITY :	▪ Multipurpose geo-spatial database, common, compatible, standardized (100s of layers) ▪ In house developed/open source software ▪ Full Utilization of available assets
AVAILABILITY:	▪ Departmental /Integrated DSS ▪ Desired Product delivery anytime, anywhere in the country
ASSIMILABILITY	▪ Integration of Various technologies like RS, GIS, GPS, Web MIS, Mobile etc.

Organizational Setup

The Institute is responsible for providing information and technical support to different Departments and Organizations. The Governing Body and the Empowered Executive Committee govern the functioning of BISAG- N. The Institute is registered under the Societies Registration Act 1860. Considering the scope and extent of activities of BISAG- N, its organizational structure has been charted out with defined functions.

Organizational Setup of BISAG- N



Governing Body

For smoother, easier and faster institutionalization of Remote Sensing and GIS technology, decision makers of the state were brought together to form the Governing Body. It is the supreme executive authority of the Institute. The Governing Body comprises of ex-officio members from various Government departments and Institutes.

- Hon'ble Minister of Electronics and Information Technology.. Chairperson (Ex-Officio)
- Hon'ble Minister of State Electronics and Information Technology....... ....Deputy Chairperson (Ex-Officio)
- Secretary of Government of India: Ministry of Electronics and Information Technology.. ....Executive Vice Chairperson (Ex-Officio)
- Chief Executive Officer, Niti Aayog.. ....Member (Ex-Officio)
- Chairman, Indian Space Research Organization ....Member (Ex-Officio)
- Secretary to Government of India: Department of Science and Technology ....Member (Ex-Officio)
- Additional Secretary to Government of India: Ministry of Electronics and Technology .. ..Member (Ex-Officio)
- Chief Secretary to Government of Gujarat.. ....Member (Ex-Officio)
- President & Chief Executive Officer, National e-Governance Division, Ministry of Electronics and Information Technology... .... Member (Ex-Officio)
- Financial Advisor to Government of India: Ministry of Electronics and Information Technology...Member (Ex-Officio)
- Distinguished Professionals from the GIS field-Three (3) (To be nominated by the Chairperson)
- Director-General, Bhaskaracharya National Institute for Space Application and Geo-Informatics {BISAG(N)} .... Member Secretary (Ex-Officio)

Centre for Geo-informatics Applications

Introduction

The objective of this technology group is to provide decision support to the sectoral stake holders through scientifically organized, comprehensive, multi-purpose, compatible and large scale (village level) geo-spatial databases and supporting analytical tools. These activities of this unit are executed by a well-trained team of multi-disciplinary scientists. The government has provided a modern infrastructure along with the state-of-the-art hardware and software. To study the land transformation and development over the years, a satellite digital data library of multiple sensors of last twenty years has been established and conventional data sets of departments have been co-registered with satellite data. The geo-spatial databases have been created using conventional maps, high resolution satellite 2D and 3D imagery and official datasets (attributes).The geo-spatial databases include terrain characteristics, natural and administrative systems, agriculture, water resources, city survey maps, village maps with survey numbers, water harvesting structures, water supply, irrigation, power, communications, ports, land utilization pattern, infrastructure, urbanization, environment data, forests, sanctuaries, mining areas, industries. They also include social infrastructure like the locations of schools, health centres, institutions, aganwadies, local government infrastructure etc. The geospatial database of nagar-palikas includes properties and amenities captured on city and town planning maps with 1000 GIS layers. Similar work for villages has been initiated as a pilot project.

The applications of space technology and geo-informatics have been operational in almost all the development sectors of the state. Remote sensing and GIS applications have provided impetus to planning and developmental activities at grass root level as well as monitoring and management in various disciplines.

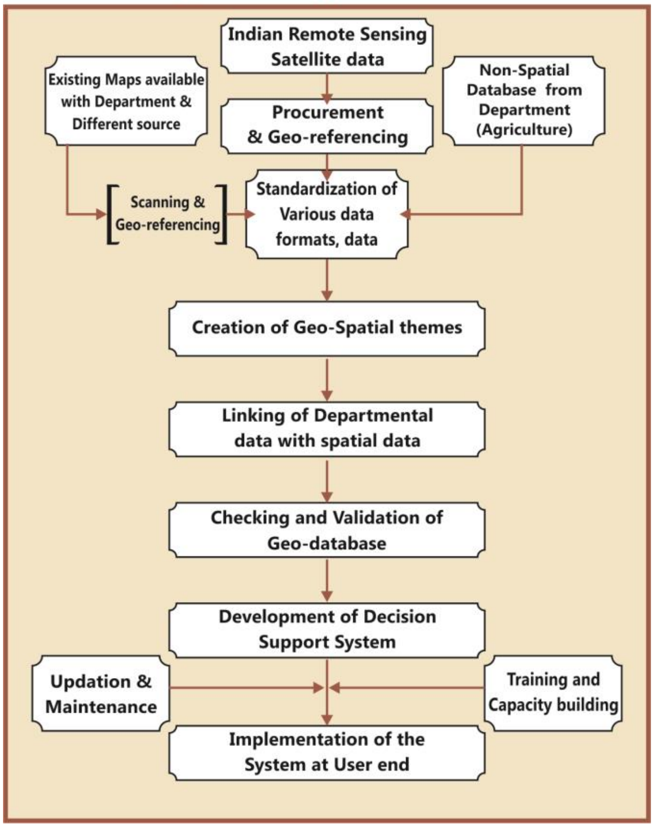
The GIS based Applications Development

The GIS software is a powerful tool to handle, manipulate and integrate both the spatial and non-spatial data. The GIS system operates on the powerful backend data base and Sequential Query Language (SQL) to inquiry the data bases. It has the capability to handle large volume of data and process to yield values of parameters which can be input to very important government activity as Decision Support System (DSS). Its mapping capabilities help the users and specialists in generating single and multi-theme wise maps.

The GIS based applications development has been institutionalized in BISAG- N. This process can be listed as (Refer Figure for Details)

- Making the users aware of the GIS capabilities through introductory training programme and by exposing to already developed projects as success stories.
- Helping the users in defining the GIS based projects.
- Digitizing the data available with the users and encouraging them to collect any additional data as may be required.
- Generating the appropriate data bases with the full involvement of the users following the data bases standards

Concept of Departmental GIS

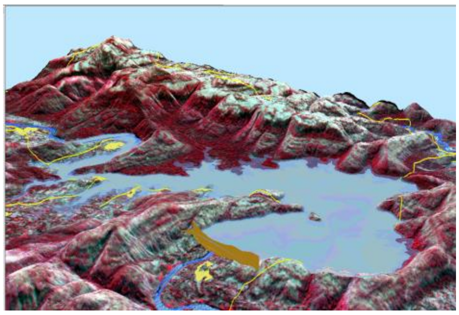


Remote Sensing and GIS Sectoral Applications:

Geo-informatics based Irrigation Management and Monitoring System

- The Geo-spatial information system for Irrigation water Management and Monitoring system for command areas in Sardar Sarovar Narmada Nigam Limited (SSNL) has been developed. Satellite image-based Irrigation monitoring system has been developed in GIS. From the multi-spectral Satellite images of every month, the irrigated areas were extracted.
- The irrigated area were overlaid on the geo-referenced cadastral maps and the statistics of area irrigated has been estimated.
- The user friendly Customized Decision Support System (DSS) has been developed.

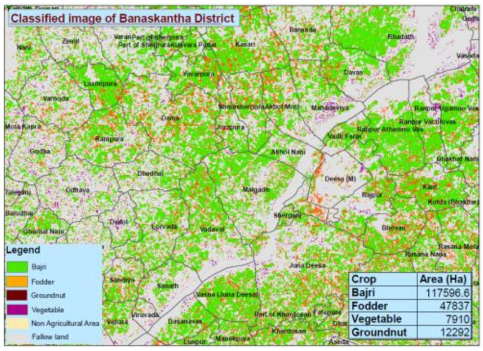
Preparation of DPR of Par–Tapi-Narmada Link using Geo-informatics for National Water development Agency (NWDA)



- The main objective of Par–Tapi-Narmada Link project is to divert surplus water available in west flowing rivers of south Gujarat and Maharashtra for utilization in the drought prone Saurashtra and Kachcha. On the request from NDWA, preparation of various maps for proposed DPR work was undertaken by the BISAG- N. Land use and submergence maps of proposed dams along with its statistics have been prepared by the BISAG- N. The detailed work consisted of generation of Digital Elevation Model (DEM), contour generation, Land use mapping, forest area generation of submergence extent at different levels etc.

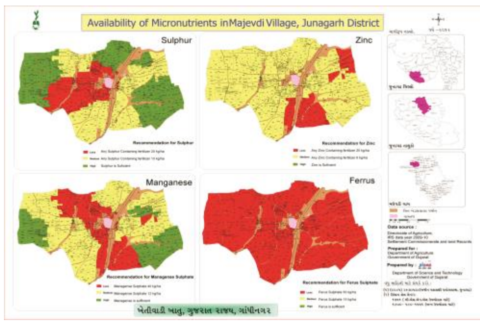
Agriculture

District and Village-level Crop Inventory



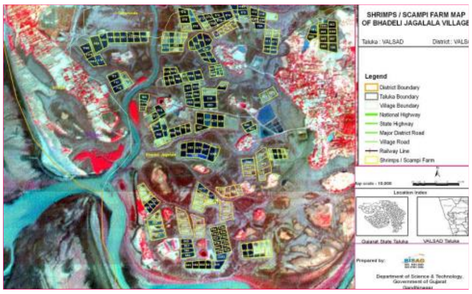
- Remote Sensing (RS) based Village-level Crop Acreage Estimation at was taken up in two villages of Anand and Mehsana districts of Gujarat state. The major objective of this study was to attempt village-level crop inventory during two crop seasons of Kharif (monsoon season) and Rabi (winter season) using single-date Indian Remote Sensing (IRS) LISS-III and LISS-IV digital data of maximum vegetative growth stage of major crops during each season.
- District-level crop acreage estimation during three cropping seasons namely Kharif, Rabi and Zaid (summer) seasons was also carried out in all the 26-districts of Gujarat State. Summer crop acreage estimation Gujarat State was carried out during 2012.

Spatial Variability Mapping of Soil Micro-Nutrients



- The spatial variability of soil micro-nutrients like Fe, Mn, Zn and Cu in various villages of different districts, Gujarat state was mapped using geo-informatics technology. The major objectives of this study were i) to quantify the variability of Mn, Fe, Cu and Zn concentration in soil; ii) to map the pattern of micro-nutrient variability in cadastral maps, iii) suggest proper application of micro-nutrients based on status of deficiency for proper crop management and iv) preparation of village-level atlases showing spatial variability of micro-nutrients.

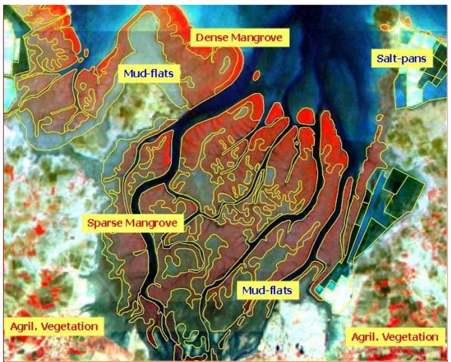
Geo-spatial Information System for Coastal Districts of Gujarat



- The project on development of Village-level Geo-spatial Information System for Shrimp Farms in Coastal Districts of Gujarat, was taken with major objective of development of Village-level Geo-spatial Information System for Shrimp/Scampi areas using Remote Sensing (RS) and GIS. This project was sponsored by the Marine Products Export Development Authority (MPEDA), Ministry of Commerce & Industry, Government of India for scientific management of Scampi farms in the coastal districts which can help fishermen to better their livelihood and increase the economic condition on sustainable basis. The customized query shell was developed using the open source software for sharing the information amongst the officers from MPEDA and potential users. This has helped the farmers to plan their processing and marketing operations so as to achieve better remunerations.

Environment and Forest

Mapping and Monitoring of Mangroves in the Coastal Districts of Gujarat State



Mangrove Density classes & mud-flats Observed along Jamnagar Coast

- Gujarat Ecology Commission, with technical inputs from the Bhaskaracharya National Institute for Space Applications and Geo-informatics - N (BISAG- N) made an attempt to publish Mangrove Atlas of the Gujarat state. Mangrove atlas for 13-coastal districts with 35-coastal talukas in Gujarat, have been prepared using Indian Remote sensing satellite images. The comparison of mangrove area estimates carried out by BISAG- N and Forest Survey of India (FSI) indicates a net increase in the area under mangrove cover. The present assessment by BISAG- N, has recorded 996.3 sq. km under mangrove cover, showing a steep rise to the tune of 88.03 sq. km. In addition to the existing Mangrove cover, the present assessment also gives the availability of potential area of 1153 sq. km, where mangrove regeneration program can be taken up.

Academy of Geo-informatics for Sustainable Development

Introduction

- Considering the requirement of high end research and development in the areas having relevance of geo-informatics technology for sustainable development, a separate infrastructure has been established. In collaboration with different institutes in the state as well as in the country, R&D activities are being carried out in the areas of climate change, environment, disaster management, natural resources management, infrastructure development, resources planning, coastal hazard and coastal zone management studies, etc. under the guidance of eminent scientists.

- Various innovative methodologies/models developed in this academy through the research process have helped in development of various applications. There are plans to enhance R&D activities manifold during coming years.
- This unit also provides training to more than 600 students every year in the field of Geo-informatics to the students from various backgrounds like water resources, urban planning, computer Engineering, IT, Agriculture in the areas of Remote sensing, GIS and their applications.

- This Academy has been established as a separate infrastructure for advanced research and development through following schools:
  - School of Geo-informatics
  - School of Climate & Environment
  - School of Integrated Coastal Zone Management

- School of Sustainable Development Studies
- School of Natural Resources and Bio-diversity
- School of Information Management of Disasters
- School of Communication and Society

During XIIth Five year Plan advance applied research through above schools shall be the main thrust area. Already M. Tech and Ph.D. students of other Universities/ Institutes are doing research in this academy in applied sciences under various collaborative programmes.

M. Tech. Students' Research Programme

The academy started M. Tech. students' research programme in a systematic way. It admitted 11 students from various colleges and universities in Gujarat, Rajasthan and Madhya Pradesh for period of 10 months from August 2011 to May 2012. All the students were paid stipend of Rs. 6000 per month during the tenure. The research covered the following areas:

- Cloud computing techniques
- Mobile communication
- Design of embedded systems
- Aquifer modelling
- Agricultural and Soils Remote Sensing
- Digital Image processing Techniques (Data Fusion and Image Classification).

The research resulted in various dissertations and publications in national and international journals.

• Now nine students, one from IIT, Kharagpur, three from GTU, one from M. S University, Vadodara and four from GU, are undergoing their Ph. D programme. Out of nine, two thesis have been submitted. Two students are from abroad. One each from Vietnam and Yemen. Since then (after approval of research programme from the Governing Body), 200+ papers have been published by the Academy.

<u>CANDIDATE'S DECLARATION</u>

I declare that 4th semester Summer Internship project report entitled "**AI Powered Tree Precision Support System for Detection and Height Measurement**" is my own work conducted under the supervision of the external guides **Dr. Yagnesh Vyas** from BISAG-N (Bhaskaracharya National Institute for Space Applications & Geo-informatics). We further declare that to the best of our knowledge the report for this project does not contain any part of the work which has been submitted previously for such project either in this or any other institutions without proper citation.

Candidate 1's Signature

Kunjalba Vala

Student ID: 24SI1

Submitted To:

Charotar University of Science and Technology

ACKNOWLEDGMENT

I are grateful to **T.P. Singh,** Director General (BISAG-N) for giving us this opportunity to work the guidance of renowned people of the field of MIS Based Portal also providing us with the required resources in the company.

I would like to express our endless thanks to our external **Dr. Yagnesh Vyas** and to Training Cell **Mr. Sidhdharth Patel** at Bhaskaracharya National Institute of Space Application and Geo-informatics for their sincere and dedicated guidance throughout the project development.

Also, my hearty gratitude to our Head of Department, **Dr. Nirav Bhatt** for giving me encouragement and technical support on the project.

Kunjalba Vala

Student ID: 24SI1

ABSTRACT

The rapid advancement in remote sensing technologies, coupled with the increasing availability of high-resolution spatial data, has revolutionized the field of environmental monitoring and management. This thesis presents a comprehensive study focused on the development and implementation of an AI-powered precision support system for tree detection and height measurement using a combination of machine learning and LiDAR data processing. The primary objective of this research is to enhance the accuracy and efficiency of forest management practices by providing precise and real-time insights into forest structure and dynamics.

The study begins by exploring the need for accurate tree detection and height measurement in the context of global environmental challenges, such as deforestation, climate change, and biodiversity conservation. Traditional methods of forest monitoring, while effective, are often labor-intensive, time-consuming, and prone to human error. These limitations underscore the importance of developing automated and scalable solutions that can deliver reliable data for informed decision-making. This thesis addresses these challenges by leveraging modern technological advancements in machine learning and 3D data processing.

The methodology employed in this research is multi-faceted, beginning with the training of a machine learning model using the Roboflow platform. A carefully curated dataset of tree images was annotated and augmented to create a robust training set, ensuring the model's ability to detect trees under various conditions. The model was then trained and optimized, resulting in a high-accuracy detection model capable of identifying trees in even urban environments.

Following the model training, the study delves into the collection and processing of LiDAR data, which is pivotal for capturing the three-dimensional structure of forested areas. LiDAR data, known for its precision and richness, was processed using the Open3D library, a powerful tool for 3D data manipulation. The data, initially stored in `.pcl` format, was converted into .las representing the physical structure of the forest. To manage the massive volume of data, downsampling techniques were applied, and the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm was employed to segment the point cloud into clusters corresponding to individual trees.

The tree clusters identified through DBSCAN were then analyzed to calculate the height of each tree, a critical metric for understanding forest dynamics. The height measurement was derived by determining the range in the Z-dimension (elevation) within each cluster, providing an accurate estimate of tree height. These measurements were essential for subsequent spatial-temporal analysis, which involved the comparison of tree heights over time using a series of temporal images captured at different intervals.

The findings of this research have significant implications for the field of forestry and environmental management. The AI-powered precision support system developed in this thesis represents a major step forward in the automation of forest and urban monitoring tasks, offering a solution that is not only accurate but also efficient and scalable. This system has the potential to transform the way forests and urban area are managed, contributing to the preservation of biodiversity, the mitigation of climate change, and the promotion of sustainable development.

In conclusion, this thesis presents a detailed study on the integration of machine learning, LiDAR data processing, for the detection and measurement of trees in forested environments. The methodologies and technologies employed in this research demonstrate the power and potential of modern AI tools in addressing some of the most pressing environmental challenges of our time. The AI-powered precision support system developed through this research offers a promising solution for the future of forest management, enabling more informed, accurate, and timely decisions in the quest to preserve and protect our planet's vital ecosystems.

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ABBREVIATIONS

1. **AUC - Area Under the Curve**
2. **A- Artificial Intelligence**
3. **CL – Classification Loss**
4. **CNN - Convolutional Neural Network**
5. **COCO - Common Objects in Context**
6. **DBSCAN - Density-Based Spatial Clustering of Applications with Noise**
7. **DFL- Distribution Focus Loss**
8. **DL - Deep Learning**
9. **FP - False Positive**
10. **FN- False Negative**
11. **GAN - Generative Adversarial Network**
12. **IoU - Intersection over Union**
13. **LiDAR - Light Detection and Ranging**
14. **mAP - Mean Average Precision**
15. **ML - Machine Learning**
16. **OBIA - Object-Based Image Analysis**
17. **R-CNN - Region-Based Convolutional Neural Network**
18. **SAR - Synthetic Aperture Radar**
19. **SSD - Single Shot Multibox Detector**
20. **TP - True Positive**
21. **UAV - Unmanned Aerial Vehicle**
22. **YOLO - You Only Look Once**

CHAPTER 1: INTRODUCTION

1.1 Background and Motivation

The global emphasis on environmental sustainability and conservation has heightened the need for advanced tools and methodologies to monitor natural resources effectively. Forests, as vital ecological systems, play a crucial role in maintaining biodiversity, regulating climate, and providing resources for human use. However, the growing threats of deforestation, climate change, and urban expansion demand more accurate and efficient methods to monitor forest health and dynamics.

Traditionally, forest monitoring relied on ground-based surveys and manual data collection, which, while effective in localized contexts, are often labor-intensive, time-consuming, and prone to human error. With the advent of remote sensing technologies and the increasing availability of high-resolution satellite imagery, the scope for monitoring vast forested areas has expanded significantly. Yet, the challenge of accurately detecting individual trees and measuring their heights from remote imagery remains.

AI and machine learning have revolutionized various fields by providing tools capable of handling complex datasets, identifying patterns, and making predictions with remarkable accuracy. In forestry, these technologies have the potential to transform how we monitor and manage forest resources. By integrating AI we can develop precision support systems that enhance our ability to detect trees and measure their heights accurately over time.

This research is motivated by the need to bridge the gap between traditional forestry methods and modern technological advancements, leveraging AI to create a system that is both accurate and scalable for global forest monitoring.

1.2 Problem Statement

The accurate detection of trees and the precise measurement of their heights are critical components of forest management, biodiversity assessment, and carbon stock estimation. However, these tasks are fraught with challenges, particularly when relying on remote sensing data. The dense canopy cover, varying terrain, and the presence of different tree species complicate the detection and measurement processes. Traditional methods, such as manual interpretation of aerial photographs or in-situ measurements, are often limited in scope and accuracy.

The main problem addressed by this research is the development of an AI-powered precision support system capable of detecting individual trees and accurately measuring their heights using spatial-temporal analysis. This system aims to overcome the limitations of existing methods by providing a scalable solution that can be applied to diverse forest environments.

Specifically, the research seeks to address the following questions:

- How can AI be utilized to improve the accuracy of tree detection in complex forest environments?
- What techniques can be employed to measure tree heights with high precision using remote sensing data?

1.3 Objectives of the Study

The primary objective of this research is to develop a comprehensive AI-powered precision support system for tree detection and height measurement that integrates spatial-temporal analysis. The specific objectives include:

1. Developing an AI-Based Tree Detection Model: Design and implement a machine learning model capable of accurately detecting individual trees from high-resolution satellite imagery.

2. Implementing Height Measurement Techniques: Develop methodologies to estimate tree heights using LiDAR data from various remote sensing sources, ensuring high accuracy and reliability.

3. Validating and Evaluating the System: Test the system in different forest environments, comparing its performance against traditional methods and assessing its potential for large-scale application.

1.4 Scope and Delimitations

This study focuses on the development and evaluation of an AI-powered system for tree detection and height measurement within a defined geographic and ecological context. The scope includes:

1.4.1 Geographic Scope

The research will be conducted in selected urban regions, which represent a variety of ecological conditions, including vegetation, buildings and roads. These regions will be chosen based on their availability of high-resolution remote sensing data and ground truth measurements.

1.4.2 Technological Scope

The study will utilize satellite imagery, LiDAR data, and other remote sensing technologies as primary data sources. Machine learning algorithms, particularly CNNs, will be employed for tree detection, while height measurement will rely on techniques such as stereo imaging and LiDAR-based estimation.

1.4.3 Ecological Scope

The focus will be on detecting trees of various species and sizes, with particular attention to how species diversity and urban density affect detection accuracy. The study will not differentiate between tree species in height measurement but will account for variations in canopy structure.

1.4.4 Delimitations

The study will also not address the economic valuation of forest resources, although the system could be adapted for such purposes in future research.

1.5 Significance of the Study

This research holds significant implications for both the scientific community and practical forest management. By developing a precision support, this study contributes to the following areas:

- **Advancement of AI in Environmental Monitoring:** The research showcases the application of AI in detecting and measuring trees with high precision, providing a blueprint for future studies in environmental monitoring and conservation.

- **Enhanced Forest Management Practices:** The system developed in this study can be employed by forest managers, conservationists, and policymakers to monitor forest health, plan sustainable logging practices, and assess the impact of environmental changes on forest ecosystems.

- **Contribution to Global Environmental Goals:** Accurate tree detection and height measurement are crucial for estimating carbon stocks and understanding the role of forests in mitigating climate change. This research supports global efforts to combat deforestation and promote reforestation by providing reliable data for decision-making.

- **Technological Innovation:** The integration of spatial-temporal analysis with AI represents a novel approach in the field of forestry, potentially leading to new methodologies and tools that can be adapted to other areas of environmental science.

CHAPTER 2: LITERATURE REVIEW

2.1 Overview of Tree Detection Techniques

2.1.1 Traditional Methods of Tree Detection

- **Ground-Based Surveys:**
    - Historically, tree detection has primarily relied on ground-based surveys, where foresters manually count and measure trees within a given plot. Techniques such as point sampling and transect methods have been commonly used. While these methods provide high accuracy at a localized level, they are labor-intensive and limited in spatial scope.

    - *Key Study:* A study by **Curtis and McIntosh (1951)** detailed the point-centered quarter method, a widely used technique in forest ecology for estimating tree density and distribution. Although accurate, it is limited by the requirement for extensive fieldwork.
- **Aerial Photography:**
    - The use of aerial photography for tree detection began in the early 20th century, offering a broader perspective compared to ground-based methods. However, manual interpretation of aerial photographs is subject to human error and can be challenging in dense forests where canopy overlap is significant.
    - *Key Study:* **Spurr (1960)** provided a comprehensive review of aerial photography techniques in forestry, emphasizing the advantages of stereoscopic views in identifying individual trees. Despite its utility, the method is limited by resolution and the need for skilled interpreters.

2.1.2 Remote Sensing Techniques for Tree Detection

- **Satellite Imagery:**
    - With advancements in remote sensing, satellite imagery has become a critical tool for large-scale tree detection. The development of high-resolution sensors, such as those onboard the Landsat and Sentinel satellites, has enabled the detection of individual trees in various environments.
    - *Key Study:* **Hansen et al. (2013)** utilized Landsat imagery to create a global forest cover change map, highlighting the potential of satellite data in monitoring tree cover over time. However, the study also noted challenges in differentiating between trees and other vegetation types in certain environments.
- **LiDAR (Light Detection and Ranging):**
    - LiDAR technology, which uses laser pulses to create detailed 3D models of forest structures, has revolutionized tree detection. LiDAR is particularly effective in penetrating forest canopies, allowing for accurate mapping of individual trees even in dense forests.
    - *Key Study:* **Dubayah and Drake (2000)** demonstrated the use of LiDAR in detecting tree height and canopy structure, providing a significant improvement over traditional methods. LiDAR's ability to capture vertical

    - forest structure is unparalleled, though it requires extensive processing and can be expensive to deploy over large areas.
- **UAV (Unmanned Aerial Vehicles):**
    - The advent of UAVs or drones has added a new dimension to remote sensing in forestry. UAVs equipped with cameras or LiDAR sensors can capture high-resolution images from low altitudes, enabling detailed tree detection over small to medium-sized areas.
    - *Key Study:* **Wallace et al. (2016)** explored the use of UAVs in forest management, highlighting their flexibility and cost-effectiveness. However, the study also pointed out limitations in coverage area and the need for regulatory compliance in UAV operations.

2.1.3 AI and Machine Learning in Tree Detection

- **Convolutional Neural Networks (CNNs):**
    - CNNs have emerged as powerful tools for image recognition tasks, including tree detection in remote sensing data. These networks can automatically learn and extract features from images, making them highly effective in identifying individual trees in complex environments.
    - *Key Study:* **Zhu et al. (2017)** applied CNNs to high-resolution satellite imagery for automatic tree crown detection, achieving high accuracy. The study demonstrated the potential of deep learning in automating tree detection processes, though it also highlighted the need for large training datasets.
- **Object-Based Image Analysis (OBIA):**
    - OBIA is a technique that segments images into meaningful objects rather than individual pixels, allowing for more accurate tree detection. This method is particularly useful when combined with machine learning algorithms to classify different vegetation types.
    - *Key Study:* **Blaschke (2010)** provided a comprehensive review of OBIA, discussing its advantages over traditional pixel-based methods in handling high-resolution imagery. The study noted that OBIA, when combined with AI, could significantly enhance tree detection accuracy, especially in heterogeneous landscapes.

2.2 Height Measurement Methodologies

2.2.1 Historical Approaches to Tree Height Measurement

- **Trigonometric Methods:**
    - One of the oldest methods for measuring tree height involves basic trigonometry. Using a clinometer or similar device, the height of a tree can be calculated by measuring the angle of elevation and the distance from the tree's base.
    - *Key Study:* **Meyer (1930)** detailed the use of trigonometric methods in forestry, emphasizing their simplicity and effectiveness in the field. Despite their reliability, these methods are limited by the need for clear sightlines and are less effective in dense forests.

- **Hypsometers and Altimeters:**
  - Hypsometers and altimeters have been traditionally used to measure tree height by calculating the vertical distance between the top and bottom of a tree. These instruments, while useful, are prone to inaccuracies due to human error and environmental factors.
  - *Key Study:* **Wheeler (1962)** reviewed the use of hypsometers in forestry, discussing their practical applications and limitations. The study highlighted the need for calibration and the potential for errors in dense canopies.

2.2.2 Ground-Based Laser Scanning (Terrestrial LiDAR)

- **TLS (Terrestrial Laser Scanning):**
  - TLS involves the use of ground-based LiDAR systems to scan trees and generate detailed 3D models. This method allows for precise measurements of tree height, trunk diameter, and canopy structure, offering a level of detail unmatched by other techniques.
  - *Key Study:* **Brolly and Király (2009)** demonstrated the use of TLS in forestry, showing its ability to accurately measure tree height and other structural parameters. The study also discussed the challenges of using TLS in dense forests, where occlusion can affect data quality.

2.2.3 Aerial and Satellite-Based Height Measurement

- **LiDAR from Airborne Platforms:**
  - Airborne LiDAR, mounted on aircraft or drones, has become a widely used method for measuring tree height over large areas. By emitting laser pulses and measuring their return time, airborne LiDAR can create precise elevation models that include tree heights.
  - *Key Study:* **Lefsky et al. (2002)** provided a foundational study on the use of airborne LiDAR in forest inventory, illustrating its effectiveness in measuring tree height and biomass. The study highlighted the advantages of airborne LiDAR in covering large areas quickly but also noted the high cost of deployment.
- **Stereo Photogrammetry:**
  - Stereo photogrammetry uses overlapping aerial or satellite images to create 3D models of the terrain and vegetation, allowing for tree height estimation. This technique is particularly useful in areas where LiDAR data is unavailable.
  - *Key Study:* **St-Onge et al. (2008)** explored the use of stereo photogrammetry in forestry, comparing it with LiDAR and finding that while it offers good accuracy, it is dependent on image quality and the density of tree cover.
- **Synthetic Aperture Radar (SAR):**
  - SAR systems, which use radar waves to penetrate vegetation, can also be used to estimate tree height. This method is less affected by cloud cover and lighting conditions, making it useful in tropical regions where optical data is often limited.
  - *Key Study:* **Kellndorfer et al. (2004)** investigated the use of SAR for forest structure analysis, showing its potential in estimating tree height in dense forests. However, the study also noted the complexity of interpreting SAR data, particularly in heterogeneous landscapes.

2.2.4 Modern AI-Based Height Estimation Techniques

- **Deep Learning for Height Estimation:**
    - Recent advances in deep learning have enabled the development of models that can estimate tree height directly from imagery. These models leverage large datasets to learn the relationship between image features and tree height, providing a powerful tool for automated height measurement.
    - *Key Study:* **Hermosilla et al. (2018)** applied deep learning to LiDAR and optical data for tree height estimation, achieving high accuracy even in challenging environments. The study highlighted the potential of deep learning to automate and scale height estimation processes, though it also emphasized the need for extensive training data.
- **Integrating Multi-Source Data:**
    - Combining data from different sources, such as LiDAR, optical imagery, and SAR, has been shown to improve the accuracy of height estimation. Machine learning models can be trained to integrate these diverse data types, leveraging their complementary strengths.
    - *Key Study:* **Hansen et al. (2019)** explored the integration of multi-source data for tree height estimation, demonstrating that combining LiDAR and optical data significantly improves accuracy. The study also discussed the challenges of data fusion, particularly in terms of aligning datasets with different resolutions and formats.

2.3 Summary of Key Findings

The literature reviewed in this chapter highlights the evolution of tree detection and height measurement techniques from traditional methods to modern AI-driven approaches. Ground-based surveys, while accurate, are limited in scope and scalability, making them less suitable for large-scale forest monitoring. Remote sensing technologies, particularly LiDAR and satellite imagery, have expanded the possibilities for tree detection and height measurement, offering high accuracy over large areas. However, these methods come with challenges related to cost, data processing, and accessibility.

The advent of AI and machine learning has brought significant advancements in tree detection and height measurement. Techniques such as CNNs and OBIA have improved the accuracy and automation of tree detection processes, while deep learning models have enabled more precise height estimation.

However, the review also reveals gaps in the literature, particularly in the integration of multi-source data and the validation of AI-driven models in diverse forest environments. These gaps present opportunities for further research, particularly in the development of more robust and scalable AI-powered precision support systems for tree detection and height measurement.

CHAPTER 3: TECHNOLOGIES USED

3.1 Python Programming Language

3.1.1 Overview and Importance in Research

Python is a versatile and powerful programming language that has become a cornerstone in the fields of data science, machine learning, and spatial analysis. Known for its simplicity and readability, Python allows researchers to rapidly prototype and deploy complex algorithms, making it an ideal choice for scientific computing. The language's extensive library ecosystem provides tools for everything from numerical analysis to image processing, making it central to this research.

Figure 3.1 Python

3.1.2 Key Libraries and Frameworks

- **NumPy and Pandas:**
  - NumPy is the foundational library for numerical computing in Python, providing support for large multi-dimensional arrays and matrices. Pandas builds on this by offering high-level data structures and analysis tools, crucial for handling and preprocessing the large datasets used in this research.
- **TensorFlow and PyTorch:**
  - For machine learning tasks, particularly the training and deployment of neural networks, TensorFlow and PyTorch are the go-to frameworks. Both libraries provide robust support for deep learning, with TensorFlow offering more production-ready tools and PyTorch being favored for research due to its flexibility.
- **Matplotlib and Seaborn:**
  - Visualization is key to understanding data trends and model performance. Matplotlib and Seaborn are Python's primary libraries for creating detailed and customizable plots, allowing for the clear presentation of research findings.

3.1.3 Application in the Research

In this research, Python is used for a variety of tasks, including data preprocessing, machine learning model development, and spatial analysis. Its role is central to the development of the AI-powered precision support system, particularly in automating tree detection and height measurement processes.

3.2 Open3D for LiDAR Data Processing

3.2.1 Overview of Open3D

Open3D is an open-source library designed for processing 3D data, including point clouds, meshes, and depth maps. It is particularly well-suited for working with LiDAR data, which is a critical component of this research. Open3D provides tools for efficient data handling, visualization, and geometric processing, making it a key technology for analyzing the 3D structure of forests.

Figure 3.2 Open3D

3.2.2 Key Features and Capabilities

- **Point Cloud Processing:**
  - Open3D excels in handling large point cloud datasets, which are often generated by LiDAR scans. It provides functions for point cloud segmentation, filtering, and feature extraction, which are essential for identifying individual trees and measuring their heights.
- **3D Visualization:**
  - One of the strengths of Open3D is its ability to visualize complex 3D data interactively. This is particularly useful for validating the results of tree detection algorithms and understanding the spatial structure of the forest canopy.
- **Geometric Operations:**
  - Open3D includes a wide range of geometric processing tools, such as surface reconstruction, mesh generation, and collision detection. These tools are used to refine the 3D models of trees and ensure accurate height measurements.

3.2.3 Application in the Research

In this research, Open3D is used to process and analyze LiDAR data, which is crucial for detecting individual trees and measuring their heights. The library's capabilities in point cloud processing and 3D visualization allow for detailed analysis of forest structures, supporting the development of accurate AI models.

3.3 Roboflow for Machine Learning Model Training

3.3.1 Overview of Roboflow

Roboflow is a platform designed to streamline the process of building and deploying machine learning models, particularly for computer vision tasks. It provides tools for dataset management, data augmentation, and model training, all within an easy-to-use interface. Roboflow is highly compatible with popular machine learning frameworks like TensorFlow and PyTorch, making it an integral part of the model development pipeline in this research.

Figure 3.3 Roboflow

3.3.2 Key Features and Capabilities

- **Dataset Management:**
    - Roboflow allows researchers to upload, organize, and version control their datasets. This is crucial for ensuring that the training data used in machine learning models is clean, well-labeled, and consistent.
- **Data Augmentation:**
    - One of Roboflow's standout features is its data augmentation capabilities. By applying transformations such as rotation, scaling, and flipping, Roboflow can generate more training data from a limited dataset, improving model robustness and performance.
- **Model Training and Deployment:**
    - Roboflow integrates seamlessly with machine learning frameworks, enabling users to train models directly on the platform. It also provides tools for deploying models to production environments, making it easier to move from research to real-world applications.

3.3.3 Application in the Research

Roboflow is used in this research to manage and preprocess the imagery data required for tree detection. Its data augmentation tools are particularly valuable in enhancing the diversity and quality of the training dataset, which in turn improves the accuracy of the machine learning models developed for tree detection and height estimation.

CHAPTER 4: METHODOLOGY

The methodology adopted in this research integrates various advanced technologies and processes to accurately detect tree structures and measure their heights. This chapter elaborates on the sequential steps, including model training, data collection, LiDAR data processing and tree height extraction. Each step is crucial in achieving the goal of developing an AI-powered precision support system for forest monitoring.

4.1 Machine Learning Model Training with Roboflow

The Roboflow dataset was sourced from its extensive data library, specifically selected for object detection tasks. This dataset provided a comprehensive collection of labeled images that were crucial for training the AI model. The dataset was split into training, validation, and test sets, ensuring that the model was trained and evaluated on distinct subsets of data to prevent overfitting and to gauge its generalization capabilities.

4.2. Model Architecture and Training Details

4.2.1 Comparative Discussion of AI Models

In this section, we explore and compare various AI models employed for tree detection. Each model's strengths and weaknesses are discussed in the context of their suitability for different applications. Below are the various models used in the field of object detection.

1. **YOLO:**

YOLO is known for its speed and real-time processing capabilities, making it suitable for applications where rapid tree detection is required, such as in large-scale forestry monitoring or urban tree surveys. The model performs a single pass over the input image to predict bounding boxes and class probabilities, significantly reducing computation time. However, YOLO may compromise on accuracy, especially in detecting small or densely clustered trees due to its coarse grid approach.

2. **Faster R-CNN:**

Faster R-CNN is highly regarded for its accuracy in object detection tasks. It operates by first generating region proposals and then classifying these proposals while refining their bounding box predictions. This two-stage process allows for precise localization of trees, even in challenging environments with overlapping canopies. Despite its accuracy, Faster R-CNN is computationally intensive, making it less suitable for real-time applications without powerful hardware.

3. **Mask R-CNN:**

Mask R-CNN extends Faster R-CNN by adding a branch for predicting segmentation masks, offering pixel-level accuracy. This feature is particularly valuable in ecological studies where understanding the shape and structure of individual trees is critical. Mask R-CNN provides a more detailed understanding of tree canopies but at the cost of increased processing time and resource requirements.

4. **SSD:**

SSD strikes a balance between speed and accuracy, making it a versatile option for tree detection. It detects objects in a single pass like YOLO but uses multiple feature maps at different scales, improving its ability to detect trees of varying sizes. However, SSD may struggle with very small objects, similar to YOLO, and its accuracy is generally lower than that of Faster R-CNN.

5. **RetinaNet:**

RetinaNet introduces the Focal Loss function, which addresses the issue of class imbalance by focusing more on hard-to-classify examples. This makes RetinaNet particularly effective in scenarios where certain tree species are rare or difficult to distinguish. The model provides a good balance between precision and recall, but like Faster R-CNN, it is more computationally demanding.

4.3 Choice of Tree Detection Model

In this study, the Roboflow 3.0 Object Detection (Fast) model was employed for tree detection. This model was selected due to its balance of speed and accuracy, optimized for real-time applications, which aligns with the requirements of this project. The model is fine-tuned using a checkpoint from the COCO dataset, known for its extensive object detection benchmarks across various categories.

The choice of Roboflow 3.0 was influenced by its ability to rapidly process large datasets while maintaining a high level of detection precision, particularly in environments with diverse tree species and varying canopy structures. Compared to traditional object detection models like YOLO, Faster R-CNN, and RetinaNet, Roboflow 3.0 offers an advantageous combination of reduced computational load and real-time processing capability, making it particularly suitable for large-scale environmental monitoring tasks.

4.3.1 Comparison with Other Detection Models

- **Speed and Efficiency:** The Roboflow 3.0 model, due to its optimized architecture, significantly reduces the time required for processing large datasets compared to models like Faster R-CNN and Mask R-CNN, which are more computationally intensive. This efficiency is crucial in scenarios requiring real-time data processing, such as in urban planning or emergency response during natural disasters.
- **Accuracy and Precision:** While Roboflow 3.0 may not surpass the pinpoint accuracy of Faster R-CNN in complex environments, its performance remains competitive. It strikes a balance between precision and recall, which is essential for detecting a wide variety of tree species and sizes. The model's checkpoint on the COCO dataset further enhances its capability to generalize across different tree types, making it a versatile choice.
- **Model Usability:** Roboflow's platform offers an intuitive interface and streamlined integration with various deployment environments, which simplifies the process of applying the model in real-world scenarios. This usability advantage makes it a preferred choice for practitioners who need to quickly deploy and iterate on object detection models.

4.3.2 Model Type: Roboflow 3.0 Object Detection (Fast)

The "Roboflow 3.0 Object Detection (Fast)" model is a state-of-the-art neural network optimized for rapid object detection tasks. This model leverages the COCO dataset checkpoint, which is a well-known dataset for object detection and segmentation, containing over 80 object categories. The model is engineered to strike a balance between speed and accuracy, making it suitable for real-time applications in detecting and measuring tree heights.

4.3.3 Model Layers and Structure

The model's architecture typically involves a series of convolutional layers designed to extract features from input images. These layers are followed by pooling layers that reduce the spatial dimensions of the data, helping the model focus on the most relevant features. The final layers often include fully connected layers that interpret these features to classify objects or predict bounding boxes.

4.3.4 Training Procedure

The model was trained using a dataset split as follows:

- **Training Set:** 70% of the data (159 images)
- **Validation Set:** 20% of the data (45 images)
- **Test Set:** 10% of the data (23 images)

Preprocessing Steps:

- **Auto-Orient:** Ensured that all images were correctly oriented before training.
- **Resize:** All images were resized to a 640x640 resolution to standardize input dimensions.

Augmentations: No additional augmentations were applied to the dataset during training, which ensured that the model learned directly from the original dataset without additional transformations that might skew the results.

The training process involved iteratively feeding the model batches of images, adjusting the model's weights to minimize a loss function, which measures the discrepancy between the predicted outputs and the actual labels. This process was repeated over 300 epochs, with the model continuously improving its detection capabilities.

4.4 Height Detection Methods Analysis

Height detection is crucial in understanding tree growth and ecosystem health. Several traditional methods are compared with the predictions to establish a baseline for performance:

1) **Triangulation:**

This method involves measuring angles and distances to estimate tree height based on basic trigonometric principles. While straightforward, it is often labor-intensive and less precise.

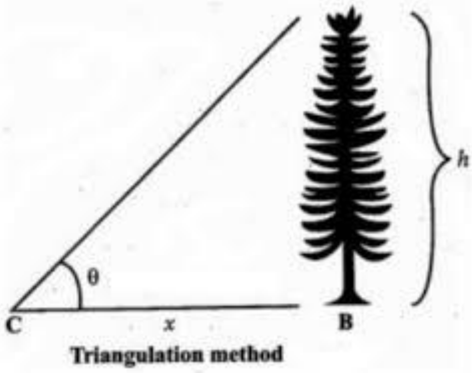

Figure 4.1 Triangulation Method

2) **LiDAR (Light Detection and Ranging):**

LiDAR technology uses laser pulses to measure distances to the earth's surface, providing highly accurate height measurements. It is considered the gold standard in remote sensing, although it is costly and requires specialized equipment.

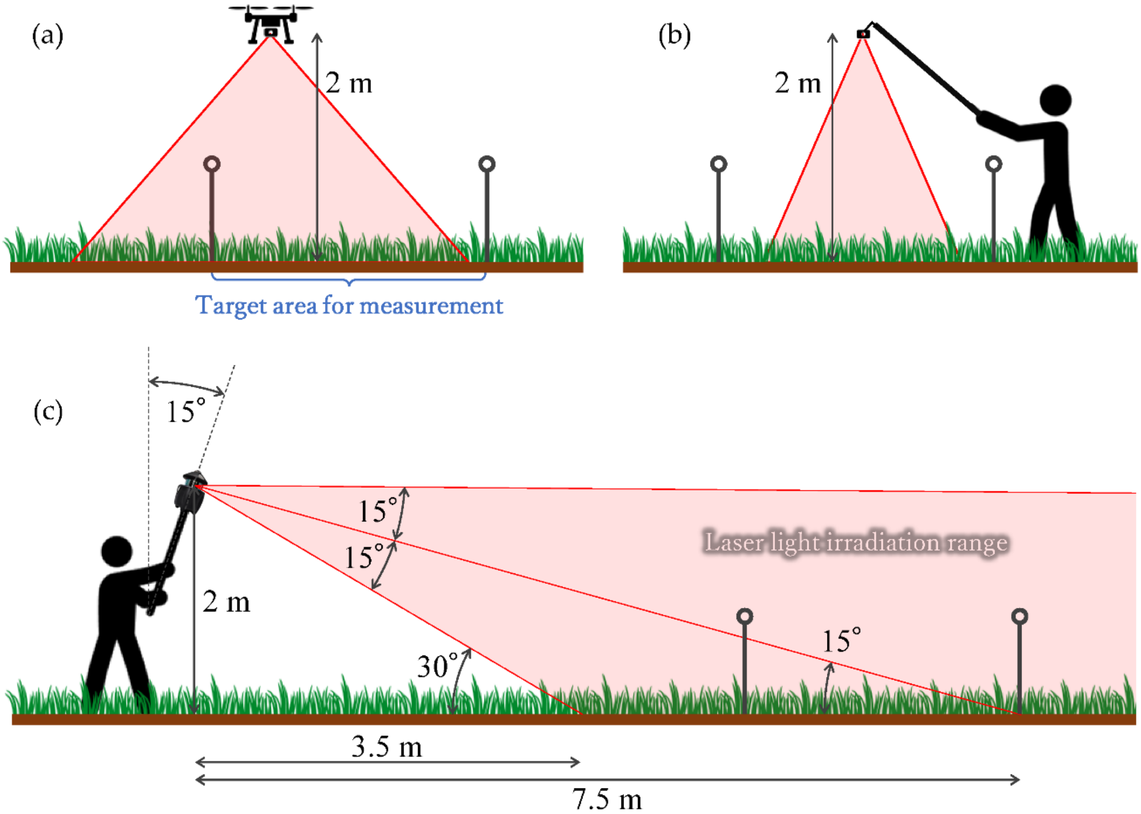

Figure 4.2 Methods of acquiring LiDAR data

Aerial Measurement using a Drone (Figure a):

The laser sensor was mounted on a drone, positioned 2 meters above the ground, to capture data directly beneath. This approach ensured wide-area coverage with minimal ground interference.

Pole-Mounted Sensor Method (Figure b):

For more controlled measurements, a laser sensor was affixed to a pole held by an operator at a 2-meter height. This method provided precise data collection over smaller areas, particularly useful for ground-level detail.

Handheld Sensor with Angled Emission (Figure c):
To extend the measurement range, the laser sensor was held by an operator at a height of 2 meters but angled at 15° upwards and downwards and 30° horizontally. This allowed for a broader coverage of 7.5 meters in length and 3.5 meters in width, making it adaptable to varied terrains and vegetation.

3) **Photogrammetry:**
This technique involves taking multiple photographs of the same area from different angles and using software to reconstruct the height of objects. It is less accurate than LiDAR but more accessible.

4) **Manual Measurement:**
Tools like clinometers and measuring tapes are used in the field to measure tree heights manually. While this method is time-consuming and subject to human error, it provides valuable ground truth data for model validation.

4.5 LiDAR Data Collection and Processing

4.5.1 Acquisition of LiDAR Data from Lidaverse

The LiDAR dataset was obtained from Lidaverse, a platform that offers high-resolution LiDAR data for various spatial analysis tasks. This dataset was critical for height measurement and 3D spatial analysis. The data was pre-processed to align with the model's input requirements, including filtering, normalization, and transformation steps necessary for accurate tree height detection.

4.5.2 Processing LiDAR Data with Open3D

The collected LiDAR data was then processed using the Open3D library, a powerful tool for working with 3D data. The steps involved in this process are as follows:

- **Reading the LiDAR Data:** The LiDAR data in .las format was imported into the Python environment using Open3D. The data was then converted into a point cloud format, where each point represents a coordinate in 3D space.
- **Filtering and Downsampling:** To manage the vast amount of data and reduce computational load, the point cloud was downsampled. This step involved selecting a subset of points that still accurately represent the tree structures while reducing the overall data size.
- **Clustering with DBSCAN:** To identify individual trees within the forest, the DBSCAN (Density-Based Spatial Clustering of Applications with Noise) algorithm was employed. DBSCAN is particularly suitable for LiDAR data as it can handle noise and varying point densities effectively. By adjusting the eps (epsilon) parameter and min_points, the algorithm was tuned to detect clusters corresponding to individual trees.

4.5.3 Height Calculation from Clusters

For each identified cluster, corresponding to a tree, the height was calculated by finding the difference between the maximum and minimum Z-coordinates of the points within the cluster. This value represents the vertical height of the tree, providing an essential metric for forest management and analysis.

4.5.4 Height Analysis Using Python Code

The core of the height analysis was implemented in Python, leveraging the processed LiDAR data and temporal images. The code performed the following steps:

- **Reading and Segmenting the Data:** The LiDAR data was segmented into clusters representing individual trees using DBSCAN, as described earlier.
- **Height Measurement:** For each tree cluster, the height was calculated by finding the range in the Z-dimension (height) within the cluster. This was then stored and analyzed to observe changes over time.
- **Data Visualization:** The results were visualized using 2D plots and 3D models, highlighting the changes in tree height and structure over the study period. This visualization provided a clear representation of the temporal changes and supported further analysis.

CHAPTER 5: RESULTS AND DISCUSSION

5.1 Evaluation Metrics for Tree Detection Models

In this section, we delve into the metrics used to evaluate the performance of the AI model developed for tree detection. These metrics provide insights into the effectiveness and accuracy of the model and help in understanding areas for improvement.

[1] Precision (P): Precision is a critical metric in the evaluation of detection models, representing the ratio of correctly identified positive observations to the total number of predicted positives. Mathematically, it is defined as:

$$\text{Precision } = \frac{TP}{TP + FP}$$

where:

- TP (True Positives) refers to the correct identification of trees.
- FP (False Positives) indicates the incorrect identification of non-tree objects as trees.

A high precision score indicates that the model has a low rate of false positives, making it reliable for applications where accuracy is critical.

[2] Recall (R): Recall, also known as sensitivity or true positive rate, measures the ability of the model to correctly identify all relevant instances. It is calculated using:

$$\text{Recall } = \frac{TP}{TP + FN}$$

where:

- FN (False Negatives) denotes the cases where actual trees are not identified by the model.

A high recall value suggests that the model is effective in detecting most of the trees in the dataset, although it may come at the cost of precision.

[3] F1 Score: The F1 Score is the harmonic mean of precision and recall, providing a single metric that balances both concerns. The F1 Score is particularly useful when dealing with imbalanced datasets:

$$F1 \text{ Score } = 2 \times \frac{\text{Precisison } \times \text{ Recall}}{\text{Precision } + \text{ Recall}}$$

[4] Mean Average Precision (mAP): Mean Average Precision (mAP) is a comprehensive metric used to evaluate object detection models. It is the average of the Average Precision (AP) scores for each class. AP is calculated as:

$$\text{AP} = \sum_{n} (R_n - R_{n-1}) P_n$$

where:

- R_n is the recall at the nth threshold.
- P_n is the precision at the nth threshold.

The mAP is then calculated as the mean of the AP scores across all classes and thresholds. For object detection tasks, mAP provides a robust indication of the model's performance across various IoU (Intersection over Union) thresholds, making it a gold standard in evaluating models.

[5] **Intersection over Union (IoU):** IoU is another fundamental metric used to evaluate the accuracy of the model's bounding box predictions. It measures the overlap between the predicted bounding box and the ground truth, calculated as:

$$IoU = \frac{\text{Area of Overlap}}{\text{Area of Union}}$$

An IoU threshold (commonly set at 0.5) is used to determine whether a predicted bounding box is a true positive. Higher IoU values indicate better performance.

5.2 Model Training and Evaluation Metrics

5.2.1 Training Graph Analysis

The training graph below showcases the Mean Average Precision (mAP) performance across 300 epochs. The mAP metric is crucial for evaluating the model's ability to accurately detect and classify objects within an image. Two curves are presented:

- **mAP**: Represents the precision and recall over all classes.
- **mAP@50:95**: Reflects the average precision calculated across different Intersection over Union (IoU) thresholds.

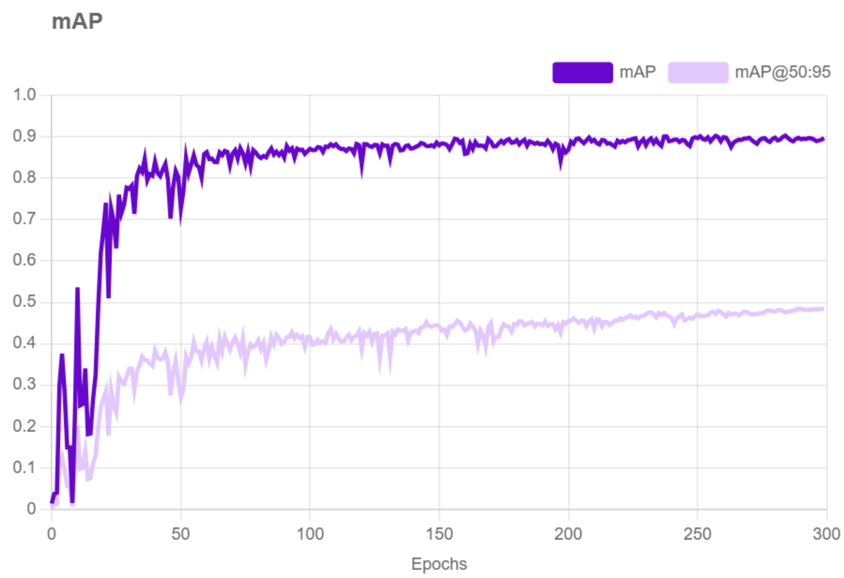

Figure 5.1 mAP of Trained model

Both curves show a significant improvement in the initial epochs, with a stabilization phase that indicates the model's convergence. The model's ability to maintain high precision over an extensive period reflects its robustness and generalization capacity.

5.2.2 Loss Functions

The loss curves represent the model's performance during training. They include:

Box Loss: Box loss measures the error in the predicted bounding box coordinates compared to the ground truth. A decreasing box loss over time indicates that the model is becoming more accurate in locating tree boundaries within the images.

Box Loss=MSE(Predicted Box−True Box)

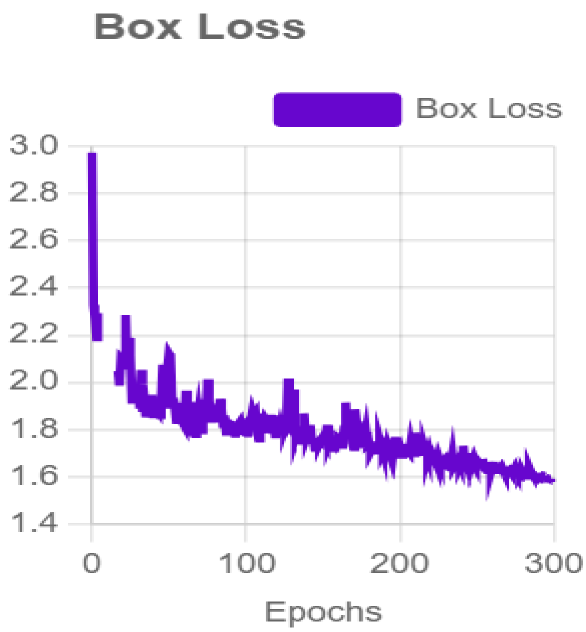

Figure 5.2 Graph of Box Loss

Classification Loss: This metric measures the difference between the predicted class probabilities and the actual class labels (i.e., tree vs. non-tree). The goal is to minimize this loss, ensuring that the model correctly identifies tree instances.

$$\text{Classification Loss } = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(p_i) + (1 - y_i)\log(1 - p_i)]$$

where:

- y_i is the actual label.
- p_i is the predicted probability.

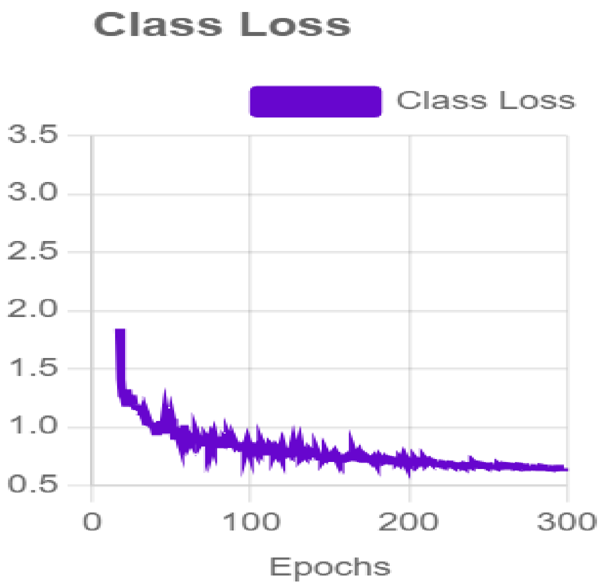

Figure 5.3 Graph of Class Loss

Object Loss: Object Loss in the context of object detection refers to the loss calculated for classifying whether a particular grid cell or bounding box contains an object or not. It is a key component of the total loss during training. It helps the model improve its confidence in detecting objects accurately within the bounding boxes it predicts. A lower object loss indicates that the model is increasingly confident in its predictions, correctly distinguishing between background and objects. The object loss is typically computed using a binary cross-entropy loss function. It evaluates the difference between the predicted objectness score and the ground truth, penalizing incorrect predictions. Mathematically:

$$\text{Object Loss } = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(\widehat{y_i}) + (1 - y_i)\log(1 - \widehat{y_i})]$$

where y_i is the ground truth (1 for object presence, 0 for background), and $\widehat{y_i}$ is the predicted probability.

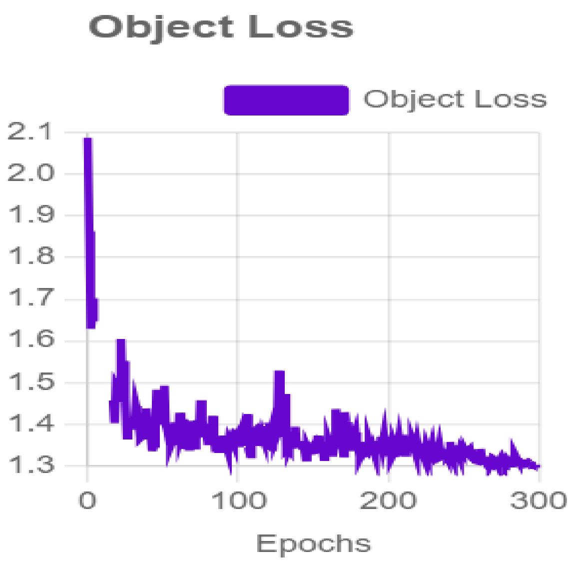

Figure 5.4 Graph of Object Loss

Precision-Recall Curves: These curves are crucial for understanding the trade-offs between precision and recall at different confidence thresholds. The area under the curve (AUC) is a key indicator of model performance, with higher values signifying better overall accuracy.

$$\mathrm{AUC} = \int_0^1 \text{Precision } \cdot d(\text{ Recall })$$

The precision-recall curve for the model indicates strong performance, with the model maintaining high precision and recall across various thresholds, demonstrating its reliability.

Over 300 epochs, these losses decrease steadily, which indicates that the model is effectively learning to improve its predictions. The slight oscillations in the loss curves towards the later epochs suggest the model's fine-tuning and stabilization. The model evaluation metrics for 300 epochs is given in table

Metric	**Value**
mAP	89.6%
Precision	92.5%
Recall	85.8%

Table 5.1 Model Evaluation Metrics

5.2.3 Epoch-by-Epoch Analysis

Each loss function shows a significant reduction during the initial 100 epochs, which suggests rapid learning. The gradual decrease in loss values after 100 epochs reflects the model's continued improvement, albeit at a slower rate, as it approaches optimal performance. The stable loss values in the final epochs indicate that the model has reached a plateau, suggesting that it has learned the best possible representation given the data and architecture.

This analysis not only demonstrates the effectiveness of the model but also highlights the challenges in fine-tuning deep learning models for specific tasks such as tree detection and height measurement.

5.3 Training and validation performance metrics

The series of graphs below represent the training and validation performance metrics over multiple epochs for a deep learning model, likely used for object detection or similar tasks. Each graph illustrates how different loss metrics and evaluation scores evolve during the training and validation phases.

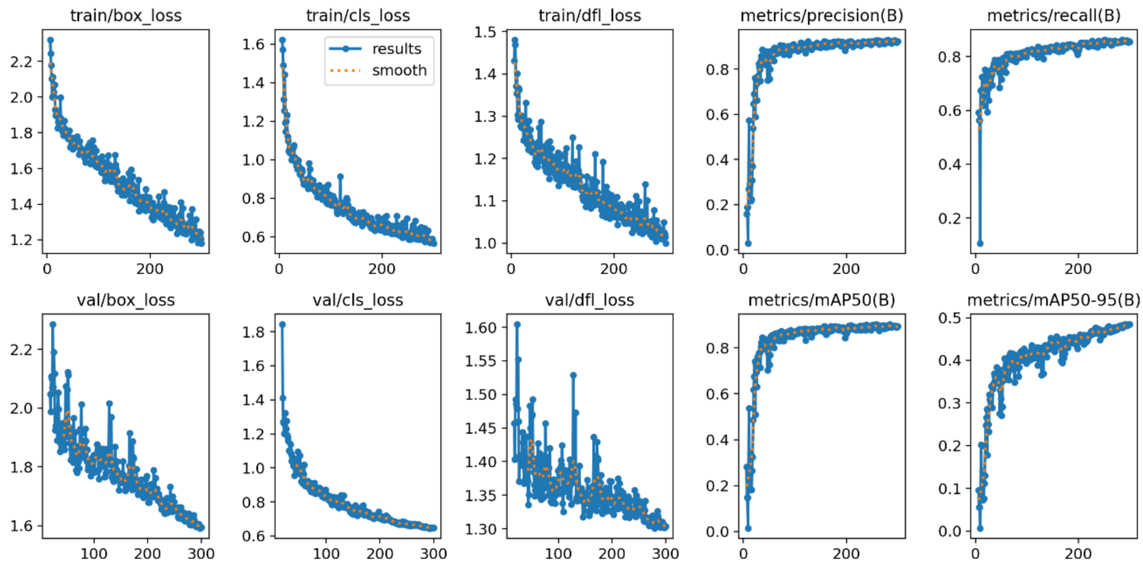

Figure 5.5 Training Graphs

1. **Train/Box Loss:** This graph shows the training loss for the bounding box regression (`train/box_loss`). The decreasing trend indicates that the model is becoming better at predicting the locations of bounding boxes around the objects as training progresses.
2. **Train/Cls Loss:** The training classification loss (`train/cls_loss`) is depicted here. A similar downward trend suggests that the model is improving in correctly classifying the objects within the bounding boxes during training.
3. **Train/DFL Loss:** The training Distribution Focal Loss (`train/dfl_loss`) is plotted, showing a steady decline. This loss is used to improve the localization accuracy of predicted bounding boxes, and the decrease reflects better performance over time.
4. **Metrics/Precision(B):** This graph displays the precision metric during training, which measures the proportion of true positive detections out of all positive detections. The increasing trend suggests that the model is improving in avoiding false positives.
5. **Metrics/Recall(B):** The recall metric during training is shown here, representing the proportion of true positive detections out of all actual positives. The curve's upward trend indicates that the model is increasingly capturing more true positives as training progresses.
6. **Val/Box Loss:** This graph shows the validation loss for bounding box regression (`val/box_loss`). The decrease, albeit with more fluctuation, reflects how well the model generalizes to unseen data.
7. **Val/Cls Loss:** The validation classification loss (`val/cls_loss`) is plotted here. Similar to the training loss, it decreases over time, suggesting better performance on unseen data but with some variability.
8. **Val/DFL Loss:** This graph represents the validation Distribution Focal Loss (`val/dfl_loss`). It shows a decrease but with noticeable fluctuations, indicating that the model's ability to accurately localize objects may vary on the validation set.
9. **Metrics/mAP50(B):** This graph illustrates the Mean Average Precision at 50% IoU threshold (mAP50) during training. The upward trend shows an improvement in the

overall detection performance, where higher precision at a fixed threshold indicates better model performance.

10. **Metrics/mAP50-95(B):** Finally, this graph shows the Mean Average Precision averaged over multiple IoU thresholds (mAP50-95) during training. The increasing trend reflects a comprehensive improvement across varying IoU thresholds, demonstrating the model's robustness in different detection scenarios.

These graphs collectively provide an overview of the model's performance during training and validation, highlighting improvements in loss functions and evaluation metrics, with some variability observed in the validation metrics indicating areas for potential further tuning or refinement.

5.4 Model Testing

The images below demonstrate the application of a tree detection model on a sample input image, yielding an output that highlights detected trees with associated confidence levels.

Figure 5.6 Input Image for Model Testing

The original image, as shown in Figure 5.6, represents a segment of a forested or urban area captured through satellite imagery. The visual content includes a diverse range of elements such as tree canopies, possibly mixed with non-vegetative elements like buildings, roads, or bare ground, depending on the image's context.

The challenge with this image lies in the complexity of accurately distinguishing trees from other objects based on various factors such as shape, color, texture, and shadow patterns.

Trees, depending on the species and the season, can exhibit varying spectral signatures, which our tree detection model must account for to achieve accurate results.

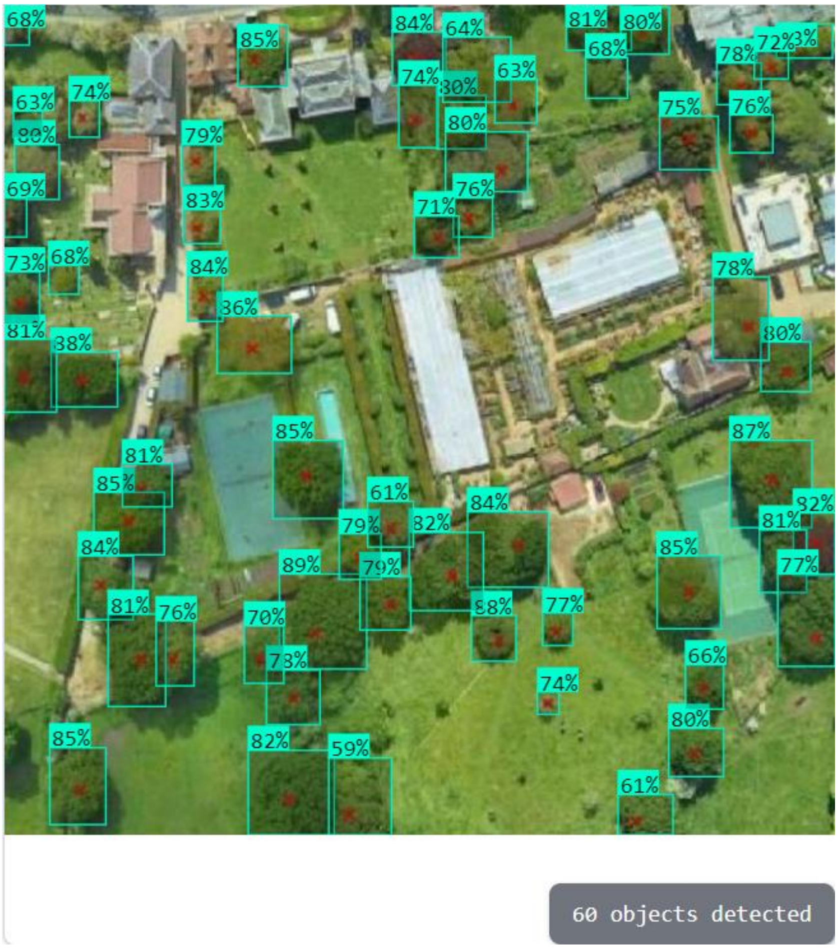

Figure 5.7 Output Image for Model Testing

In contrast, the processed output image in Figure 5.7 illustrates the results of the tree detection model applied to the input image. The algorithm has identified regions within the image that it classifies as tree canopies, which are highlighted with bounding boxes. Each bounding box is labelled with a percentage value, representing the confidence level of the detection. At the bottom right corner of the Figure 5.7 we can see the count of the detected trees as well.

The confidence values are a critical aspect of the detection process. They are typically derived from a machine learning model trained on a vast dataset of annotated images. The model evaluates various features of the image, such as pixel intensity, color distribution, and spatial arrangement, to ascertain the likelihood of a region containing a tree.

- **Bounding Boxes and Confidence Levels**:
  - The output image is overlaid with numerous bounding boxes, each surrounding a region that the model identifies as a tree canopy.
  - The confidence level, displayed as a percentage within each box, quantifies the model's certainty that the enclosed region is indeed a tree. High confidence values (e.g., 85% and above) suggest strong model agreement

with the presence of a tree, whereas lower values indicate areas where the model was less certain, potentially due to ambiguities in the image data or overlap with non-tree elements.

- **Detection Performance and Interpretation**:
  - The distribution of the bounding boxes across the image provides insights into the spatial arrangement and density of trees within the analyzed area.
  - In areas where trees are densely packed, bounding boxes might overlap or appear close together, reflecting the complex canopy structure. Conversely, isolated trees or those in sparse clusters will have distinct, separate bounding boxes.
  - The confidence levels help in further refining the analysis. For example, regions with consistently high confidence levels across multiple detections indicate strong algorithm performance, while clusters of lower confidence detections might warrant closer inspection or suggest areas for algorithm improvement.

5.5 Visualization of Tree Clusters with Height Coloring

The 3D visualization of tree clusters with height coloring provides a clear and intuitive understanding of the spatial distribution of tree heights within the study area. The visualization employs a color gradient, with colors ranging from blue (indicating lower heights) to red (indicating higher trees). This gradient helps in identifying patterns and anomalies in tree height distribution.

- **Description:**
  - The 3D scatter plot visually represents the spatial distribution of detected tree clusters within the study area. The three axes represent the X and Y coordinates (spatial location) and the Z-axis (tree height).
  - The color coding in the scatter plot highlights the variation in height across different tree clusters, providing an immediate visual cue for understanding the distribution of taller vs. shorter trees.

- **Overview:** This visualization is crucial for spatial analysis, helping to identify areas with dense tree clusters and assess their heights. The plot also allows for understanding the variation in tree heights across the study area, which can inform decisions on environmental management, urban planning, or reforestation efforts.

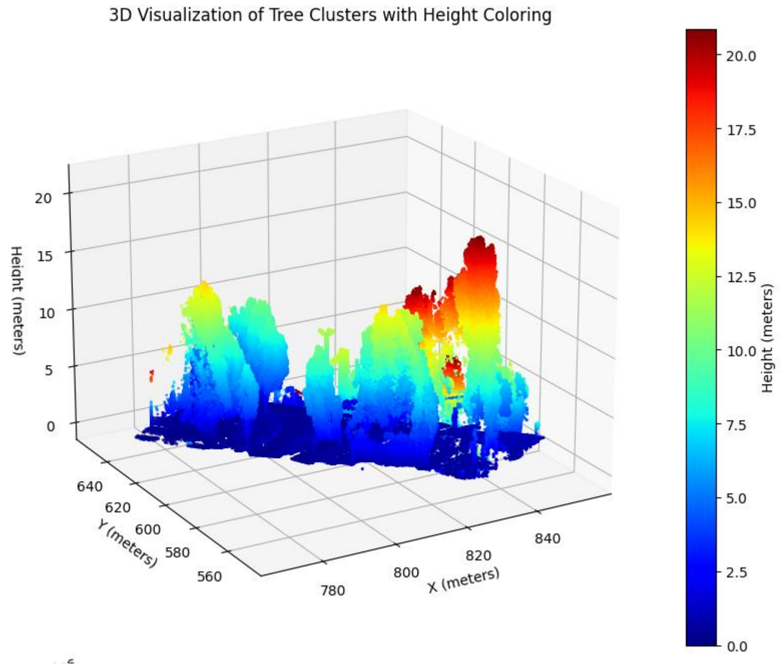

Figure 5.8 Tree Cluster with Height Coloring

Histogram of tree Heights:

- **Description:** The histogram shows the distribution of tree heights across the detected clusters. Each bar in the histogram corresponds to a specific height range, with the height of the bar representing the number of trees within that range.

- **Overview**: The histogram presents the frequency distribution of tree heights in the analyzed dataset. Each bar represents the number of trees falling within specific height intervals (e.g., 0.0–2.5 meters, 2.5–5.0 meters, etc.).

- **Data Distribution**:

    - The majority of trees fall within the lower height categories, with the most significant number having heights between 0.0 and 2.5 meters.
    - The frequency decreases as tree height increases, indicating that taller trees are less common in the dataset.

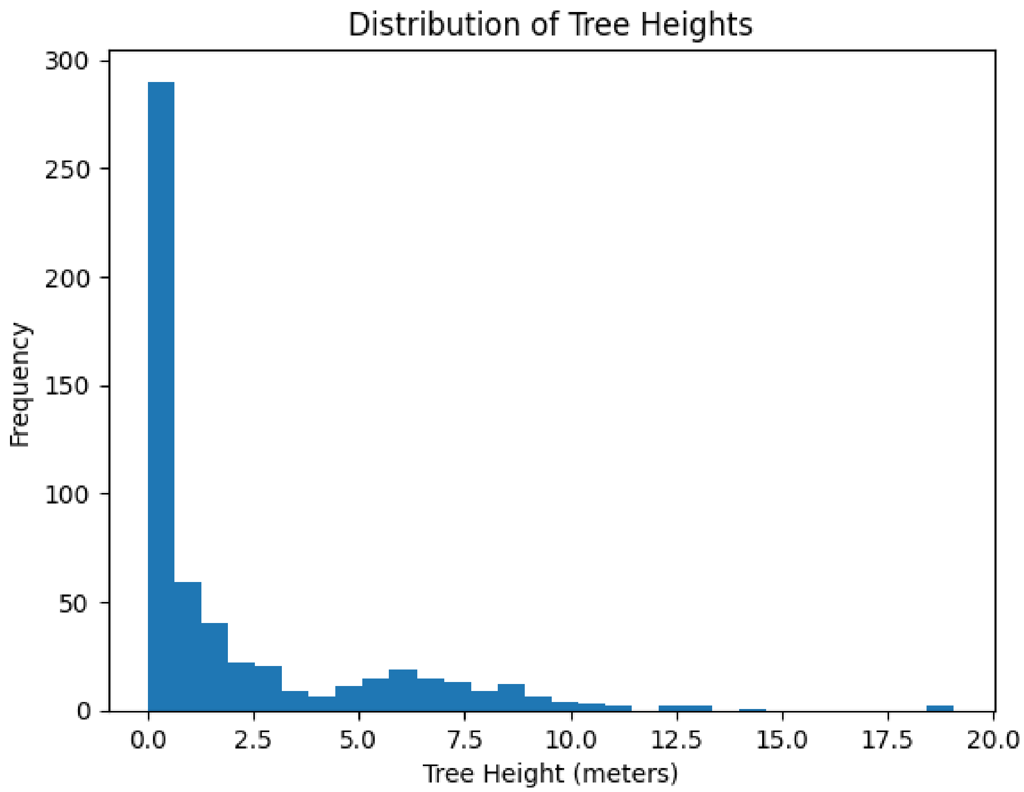

Figure 5.9 Distribution of Tree Heights

This histogram provides a statistical summary of the height distribution, which can be useful for various analyses, such as understanding the age distribution of trees, the overall health of the forest, or identifying outliers (extremely tall or short trees).

Technical Implementation:
The visualization was generated using the matplotlib library in Python, which was chosen for its flexibility and ease of integration with spatial data. The dataset, containing the 3D coordinates of trees along with their heights, was processed to create a mesh grid representing the study area.

Interpretation:
The visualization reveals that taller trees tend to cluster in specific areas, which could be attributed to favorable growing conditions or specific species distributions. Shorter trees are more dispersed, indicating variability in growth patterns. This spatial insight is crucial for urban planning, forestry management, and ecological studies.

Significance:
This method of visualization not only aids in the understanding of spatial dynamics but also serves as a tool for stakeholders, such as urban planners and conservationists, to make informed decisions regarding tree management and preservation.

CHAPTER 6: LIMITATIONS

While the AI-powered tree detection and height measurement system presented in this thesis shows great potential, several limitations need to be acknowledged, especially in the context of implementing such technology in India.

6.1 Challenges in Acquiring LiDAR Datasets

One of the most significant limitations faced in this research is the difficulty in acquiring high-quality LiDAR datasets. LiDAR is essential for generating accurate digital elevation models and for validating the height measurements obtained by the AI model. However, in India, access to such datasets is limited due to several factors:

- **Cost:** LiDAR technology is expensive, and the high cost of equipment and data acquisition limits its widespread use, especially in resource-constrained settings.
- **Data Availability:** In India, comprehensive LiDAR datasets are not readily available for all regions. This lack of data poses a significant challenge, particularly for large-scale projects that require extensive geographical coverage.
- **Regulatory Hurdles:** There are regulatory challenges related to the acquisition and use of LiDAR data in certain regions of India. Obtaining the necessary permissions can be a lengthy and complex process, further delaying research and implementation efforts.

These challenges make it difficult to train the AI model on high-resolution data, potentially impacting the accuracy of tree height measurements in regions where LiDAR data is not available.

6.2 Difficulties in Training on Large Datasets

Training AI models for tree detection and height measurement requires large datasets to ensure robustness and accuracy. However, there are several limitations associated with this requirement:

- **Data Scarcity:** In many parts of India, there is a lack of comprehensive datasets that include annotated tree data. Without sufficient training data, the model's performance can be significantly hindered, leading to less accurate predictions.
- **Computational Resources:** Training models on large datasets demands substantial computational power, which may not be readily available in all research settings. High-performance computing infrastructure is often required, and the costs associated with accessing such resources can be prohibitive.
- **Data Imbalance:** The available datasets may be imbalanced, with certain tree species or regions underrepresented. This imbalance can lead to biased models that do not perform well in diverse environments or on underrepresented species.

These limitations highlight the need for collaboration and data-sharing initiatives to build comprehensive datasets that can be used to train more accurate and generalizable models.

These limitations suggest several directions for future research:

- **Data Collaboration:** Establishing collaborations between research institutions, government agencies, and private organizations could help build more comprehensive and accessible datasets, particularly in regions where data is scarce.
- **Alternative Methods:** Exploring alternative methods for tree detection and height measurement, such as the use of satellite imagery or photogrammetry, could help mitigate the reliance on LiDAR data.
- **Model Adaptation:** Developing models that can adapt to smaller or less comprehensive datasets without compromising accuracy will be crucial for making AI-powered systems more widely applicable.

In conclusion, while the AI system developed in this thesis demonstrates significant promise, these limitations must be addressed to fully realize its potential in real-world applications, particularly in the context of India. Addressing these challenges will require ongoing research, collaboration, and innovation in both data acquisition and model development.

CHAPTER 7: CONCLUSION AND FUTURE WORK

This thesis has explored the development of an AI-powered tree detection and height measurement system. Through comprehensive analysis, the research has demonstrated the feasibility and effectiveness of AI in these areas, while also highlighting key challenges and limitations.

7.1 Conclusion

The AI-based system developed in this research has shown significant promise in accurately detecting trees and estimating their heights. The use of advanced deep learning models has enabled the processing of complex datasets, providing results that are comparable to traditional methods like LiDAR, albeit with certain limitations due to the unavailability of large-scale and high-resolution datasets, particularly in India. The system's application to deforestation detection further underscores its potential in environmental monitoring and management, offering a scalable and cost-effective solution to track forest cover changes over time.

The research has also provided insights into the performance of various object detection models, such as YOLO, Faster R-CNN, and Mask R-CNN, in the context of tree detection. While each model has its strengths and weaknesses, the choice of model should be tailored to the specific requirements of the application, balancing factors like speed, accuracy, and computational resources.

However, the study also recognizes significant limitations, including the challenges of acquiring LiDAR datasets, the computational demands of training on large datasets, and the difficulties in accessing historical data for change detection. These limitations present obstacles to the wider application of AI-based tree detection and height measurement systems, particularly in regions like India, where data availability and resource constraints are significant concerns.

7.2 Future Work

The findings of this thesis lay the groundwork for several avenues of future research and development:

1. **Data Acquisition and Collaboration:** Future research should focus on developing partnerships with governmental and non-governmental organizations to improve access to LiDAR and other remote sensing datasets. Collaborative efforts could help build a more comprehensive and standardized database of tree information across different regions of India, enhancing the system's applicability and accuracy.
2. **Integration of Alternative Data Sources:** To mitigate the reliance on LiDAR, future work could explore the integration of alternative data sources, such as high-resolution satellite imagery, UAV (drone) data, and photogrammetry. These sources could provide complementary data, helping to fill gaps where LiDAR is unavailable or cost-prohibitive.

3. **Improving Model Efficiency:** There is scope for improving the efficiency and accuracy of the AI models by experimenting with newer architectures, such as transformers, and leveraging transfer learning from pre-trained models. Additionally, exploring methods to reduce the computational load, such as model pruning and quantization, could make the system more accessible in resource-limited environments.
4. **Historical Data Reconstruction:** Given the challenges in accessing historical datasets, future research could investigate methods for reconstructing past forest cover using AI. Techniques such as Generative Adversarial Networks (GANs) could be used to simulate historical data based on current trends, providing a basis for change detection even in the absence of detailed records.
5. **Field Validation and Deployment:** Finally, field validation of the AI system in diverse ecological and geographical settings across India is crucial. Such efforts would not only help refine the model but also demonstrate its practical utility in real-world applications. Deploying the system in pilot projects for urban planning, forest management, and conservation could provide valuable feedback and drive further improvements.

7.3 Closing Remarks

In conclusion, this thesis has demonstrated the potential of AI in revolutionizing tree detection, height measurement, and deforestation monitoring. While there are challenges to overcome, particularly in terms of data availability and model scalability, the research has laid a solid foundation for future advancements in this field. By continuing to explore new data sources, improving model efficiency, and fostering collaboration, the AI-powered system developed in this study could play a critical role in sustainable environmental management and conservation efforts in India and beyond.

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