

OBJECT DETECTION USING DEEP LEARNING TECHNIQUES: A CASE STUDY OF PART OF IBADAN OYO STATE NIGERIA.

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ABSTRACT

This project explores the application of deep learning techniques in the field of geospatial analysis, specifically focusing on the detection of buildings and roads within high-resolution satellite imagery. The research methodology involves data acquisition from diverse sources, the implementation of deep learning models within the ArcGIS Pro environment, and a comprehensive accuracy assessment using visual inspection. The results indicate a notable 83% recall rate for building detection, demonstrating the model's capacity to identify a significant proportion of actual buildings. Precision values for building detection are not reported in this study. In contrast, the project achieves remarkable precision and recall rates both at 95% for road detection, illustrating the model's exceptional accuracy in identifying road networks within geospatial imagery. In summary, this project underscores the potential of deep learning integration in ArcGIS Pro for object detection tasks. While the study presents areas for improving building detection precision, the outstanding performance in road detection suggests practical applications in geospatial analysis. Future recommendations encompass model refinement, data quality enhancement, scalability exploration, and comprehensive documentation for advancing similar endeavors.

1. INTRODUCTION

Deep learning has had a profound impact on the domain of computer vision, revolutionizing the way image recognition tasks are approached and accomplished (Liu, Wang et al. 2017). It has provided data scientists with powerful tools that have significantly enhanced their ability to accurately classify images, detect objects

Overall, deep learning has not only improved the accuracy and performance of computer vision systems but also fostered innovation and pushed the boundaries of what is possible in the field (Khan, Yairi et al. 2018). Its ability to automatically learn from data and extract meaningful representations has significantly advanced the capabilities of computer vision, paving the way for exciting opportunities and advancements in the realm of data science. Deep learning (DL) algorithms have gained significant attention in the machine learning field due to their ability to learn hierarchical representations that capture meaningful and discriminative features from data. This development has extended to the geoscience and remote sensing (RS) community, where DL has been employed for analyzing RS big data (Khelifi and Mignotte 2020). In Remote Sensing applications, DL models can be utilized to extract high-level features by considering low-level features like spectral and texture information as the foundation (Miao, Xia et al. 2022). The output feature representation from the top level of the DL network can be directly inputted into a subsequent classifier for pixel-based classification. This approach allows for efficient and accurate classification of pixels in RS data (Sun, Di et al. 2019). Deep learning in remote sensing continued to evolve through ongoing research and advancements. It found applications in various domains, including change detection, land cover mapping, urban planning, disaster response, and environmental monitoring. Researchers focused on addressing challenges specific to remote sensing, such as limited labeled data, interpretability of models, computational efficiency, and adaptation to different sensors or geographic regions (Hong, He et al. 2021). The availability of open-source deep learning libraries like TensorFlow and PyTorch, along with remote sensing datasets such as the ISPRS benchmark datasets, contributed to the wider adoption and exploration of deep learning techniques in remote sensing and with the adaptation of successful methodologies from computer vision (Haut, Paoletti et al. 2021). Deep learning had already shown remarkable success in tasks such as image classification and object detection in computer vision (Liu, Ouyang et al. 2020). Researchers quickly recognized the potential of these techniques for addressing the challenges specific to remote sensing, such as the need for accurate and automated analysis of increasingly large and complex satellite imagery datasets (Dronova 2015). One key aspect of deep learning that played a crucial role in its integration into remote sensing is transfer learning. Researchers realized that pre-trained models from large-scale visual recognition datasets, such as ImageNet, could be leveraged and fine-tuned for specific remote sensing tasks. This approach enabled the transfer of learned features from general visual representations to the remote sensing domain, overcoming the challenge of limited labeled data in remote sensing (Radford, Kim et al. 2021). The integration of deep learning techniques into remote sensing was driven by the success and

advancements made in computer vision. The ability of deep learning models, especially CNNs, to learn hierarchical representations and handle large-scale datasets provided a powerful tool for automated feature extraction, object detection, and recognition from satellite imagery (Zhao, Zheng et al. 2019). Ongoing research continues to push the boundaries, leading to improved analysis and understanding of Earth's surface and environment through deep learning in remote sensing. It has gained prominence in remote sensing due to its ability to automatically learn hierarchical representations of data, handle large-scale and high-dimensional datasets, and perform end-to-end learning without the need for manual feature engineering (Song, Sui et al. 2021). These advantages have led to significant improvements in various remote sensing applications, including feature extraction, object detection, classification, change detection, environmental modeling, and disaster response.

1.1. STATEMENT OF PROBLEM

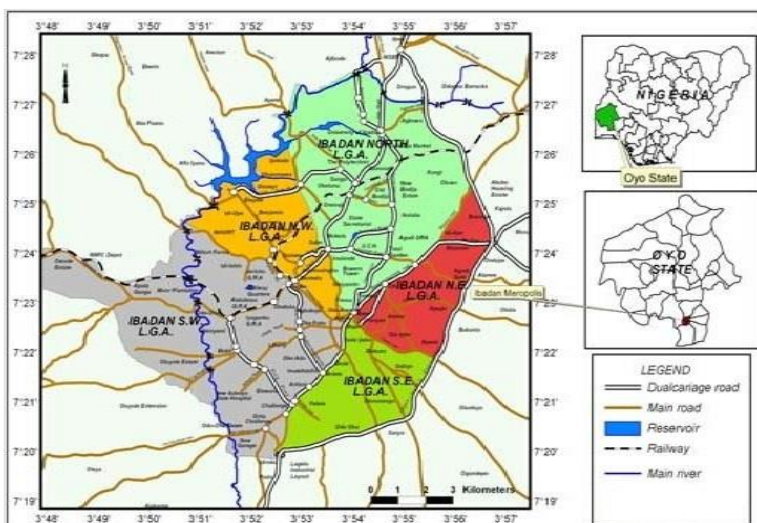
Object detection and recognition in satellite imagery play a pivotal role in various fields, including urban planning, environmental monitoring, and disaster response. However, traditional methods often rely on manual features and struggle with large datasets and complex environments. In Ibadan, Nigeria, there is a pressing need to explore the potential of deep learning techniques to address these challenges. Ibadan's unique urban landscape presents distinct challenges, with a dense population, rapid development, diverse object classes, occlusions, shadows, and intricate structures. Deep learning models must accurately identify and locate objects amidst these complexities. Additionally, Ibadan's geospatial diversity, encompassing urban areas, agricultural lands, and natural features, requires deep learning models to adapt to varying object types and scales. Addressing these challenges holds the promise of advancing deep learning for object detection and recognition in Ibadan's satellite imagery. Developing accurate, efficient, and interpretable deep learning models will enhance urban planning, environmental monitoring, and disaster response by detecting crucial features like building footprints. This, in turn, will empower better decision-making and contribute to sustainable development in Ibadan.

1.2. AIM

The research aims to develop and optimize deep learning models that can accurately identify and localize objects in satellite imagery, thereby contributing to advancements in the field of remote sensing.

1.3. OBJECTIVES

- To review the existing literature on deep learning techniques for object detection and recognition from satellite imagery. This will involve studying the various methodologies, algorithms, and architectures employed in previous research studies.
- To collect and preprocess a comprehensive dataset of satellite imagery relevant to the research context. This will involve acquiring high-resolution satellite images covering a specific geographic area and shape file of the Ibadan 4 local government.
- To design and develop deep learning models suitable for object detection and recognition on satellite imagery that is Convolutional Neural Networks (CNNs) using the ArcGIS Pro Deep Learning Libraries.
- To assess the performance of the developed deep learning models in comparison to Google Satellite imagery download by carrying out Accuracy Assessment



Ibadan's geographical location is advantageous, featuring picturesque hills, fertile lands, and proximity to major transportation routes. These factors underpin the city's status as a pivotal cultural, educational, and commercial hub in southwestern Nigeria. Situated at approximately 7.3782° N latitude and 3.9470° E longitude, Ibadan is divided into several local government areas (LGAs), as illustrated in the map below.

2. METHODOLOGY FLOW

Data Preparation: Together with my team, I start by collecting and organizing the imagery needed for analysis. We ensure that all necessary satellite or aerial images are properly loaded into ArcGIS Pro for processing.

Preprocessing: In this stage, I collaborate with my colleagues to perform preprocessing tasks like atmospheric correction, noise reduction, and radiometric correction to enhance the imagery. This ensures the data is clean and suitable for segmentation.

Image Segmentation: Once the data is prepared, I lead the segmentation process, dividing the image into meaningful segments based on pixel values, spectral properties, textures, or other features. We work together to determine the best approach based on the project's specific requirements.

Model/Tool Selection: I select the most suitable tool or method for segmentation. ArcGIS Pro offers several built-in tools like the "Segmentation" and "Classify" tools, and in collaboration with my team, we might also explore custom models that are tailored to our specific needs.

Segmentation Execution: After selecting the appropriate tool, I execute the segmentation process. Depending on the complexity of the data, the team works together to monitor the progress and ensure everything is running smoothly.

Review and Refinement: Once the segmentation is complete, I work with my team to review the results. If necessary, we adjust parameters and re-run the segmentation to refine the output and ensure that it meets the project's goals.

Post-processing: After the initial segmentation, we perform post-processing tasks such as classifying segments, merging or splitting segments, or further refining the data based on our project requirements.

Data Integration: We integrate the segmented data with other relevant layers or datasets in ArcGIS Pro, working collaboratively to enhance the analysis and provide a more comprehensive view of the project.

Visualization and Interpretation: Finally, I work with my colleagues to visualize the segmented results and interpret the patterns within the data. Together, we create maps, charts, and reports to communicate our findings clearly and effectively to stakeholders.

2.1. Data Downloading

Satellite imagery was obtained using the Tile+ plugin for QGIS. The plugin allows users to add various base maps and Earth data sources to QGIS.

- **Installing Deep Learning Framework:** Deep learning frameworks, including PyTorch, TensorFlow, Fast.ai, and scikit-learn, were installed for geospatial deep learning tasks. The installation process involved extracting a ZIP file and running the installer.
- **Object Detection with Deep Learning:** Geospatial deep learning models were downloaded from Esri's living atlas platform. These models included building extraction and road extraction models.

2.2. Detecting Objects Using Deep Learning: This "Detect Object Using Deep Learning" tool within ArcGIS Pro's Image Analyst extension was used to perform object detection. The process involved configuring parameters, selecting the input raster, specifying the output location, choosing the deep learning model, and setting confidence thresholds and class labels.

2.3. Map Refinement: Topology-based Map Refinement: Map refinement was carried out using topology in ArcGIS Pro to ensure data integrity and adherence to specific rules. The steps included creating a new topology, adding feature classes (building footprint and road), defining topology rules, validating the topology, reviewing and correcting errors, entering an editing session to make necessary edits, revalidating the topology, and repeating the process until the data met the desired quality and topology rule conformity.

2.4. Accuracy Assessment

The accuracy of geospatial data or model results using visual inspection. Here's a summary of the key steps involved:

Visual Inspection for Accuracy Assessment:

- **Visualize Data:** Randomly select 40 points on the satellite imagery, covering the entire area of interest.
- **Conduct Visual Comparison:** Compare the detected objects from the deep learning model to the reference points on the satellite imagery.
- **Categorize Detected Objects:**
 - **True Positive (TP):** Detected objects that correctly match the reference points on the satellite imagery.
 - **False Positive (FP):** Detected objects that do not correspond to any reference points.
 - **False Negative (FN):** Reference points that the model fails to detect.

- **Categorize Errors:** Identify and categorize the types of errors observed during visual inspection. Common categories include omission errors (features missing in the assessed data), commission errors (incorrectly added features), and positional errors (misplacement of features).
- **Assess Error Impact:** Consider the impact of the identified errors on the intended use of the data or results. Some errors may have a minor impact and may not significantly affect the overall analysis, while others may have a more significant impact on decision-making.

Visual inspection provides a qualitative assessment of accuracy by visually comparing detected objects to reference points. While it may not provide precise quantitative metrics, it allows for a qualitative understanding of the model's performance and the quality of the geospatial data. This assessment is important for evaluating the reliability of the object detection results and understanding how errors may impact the overall analysis and decision-making process.

3. ANALYSIS AND RESULTS

The objective of this study forms the basis of all the analysis carried out in this chapter. In this chapter, the outcome of the study is presented and discussed in detail sequentially. Starting from the data acquisition to adopting the deep learning techniques Most of the discussions are supported by maps, tables and charts. After collecting all the relevant primary and secondary data, the next task was to process and analyzing the data. As discussed earlier this study applies object detection using deep learning techniques in the ArcGIS environment.



Figure 1: Satellite Imagery

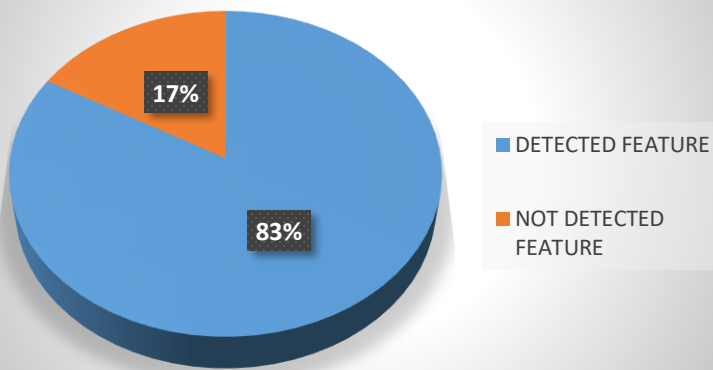


Figure 2: Detected Features

ACCURACY ASSESSMENT RESULT

FID	Shape	Feature	Detection	Easting_m	Northing_m	RASTERVALU
0	Point	Building	TP	433307.3225	830833.6124	215.322
1	Point	Building	TP	434037.6671	830839.4669	117.634
2	Point	Building	TP	434484.8019	830870.2029	229.73
3	Point	Building	TP	435485.1838	830807.9992	147.939
4	Point	Building	TP	435618.6364	830257.4159	114.149
5	Point	Building	TP	434887.2965	830220.3571	130.035
6	Point	Building	TP	433819.7169	830216.4465	219.358
7	Point	Building	TP	433217.8369	830075.2249	204.969
8	Point	Building	TP	432546.6993	830053.5049	7.09443
9	Point	Building	TP	432551.3645	829153.9662	161.59
10	Point	Building	TP	432843.356	829113.1313	80.7349
11	Point	Building	TP	433662.2495	828870.1709	112.202
12	Point	Building	TP	434006.8854	828823.1522	203.676
13	Point	Building	TP	435058.8598	828956.9359	94.4926
14	Point	Building	TP	435701.4789	828974.0877	91.8
15	Point	Building	TP	435545.9696	828239.9925	161.035
16	Point	Building	TP	434178.403	828010.159	77.808
17	Point	Building	FN	433473.4429	827969.315	139.703
18	Point	Building	TP	432821.7753	827868.6252	181.631
19	Point	Building	FN	432557.9508	827840.5167	122.315
20	Point	Road	TP	432536.4082	827607.6645	18.0914
21	Point	Building	TP	432854.2874	827643.1114	109.461
22	Point	Building	TP	433270.7613	827673.0204	209.553
23	Point	Building	TP	433678.3492	827610.7289	185.098
24	Point	Building	TP	434353.3509	827663.6935	50.681
25	Point	Road	TP	435421.8281	827613.7866	123.557
26	Point	Road	TP	435702.0812	827462.21	90.8342
27	Point	Road	TP	435687.1199	827163.2442	88.2834
28	Point	Building	TP	435569.8715	827073.9121	79.636
29	Point	Building	TP	434896.2171	826792.6557	123.76
30	Point	Building	TP	434389.0079	826605.434	232.788
31	Point	Building	TP	434174.3198	826683.8122	121.916
32	Point	Building	TP	433427.3415	826665.0696	163.974
33	Point	Building	FN	432845.9416	826692.855	225.602
34	Point	Building	TP	432705.4442	827026.0183	200.374
35	Point	Building	TP	433211.4266	828476.3557	183.067
36	Point	Building	TP	432872.2875	828485.0795	122.216
37	Point	Building	FN	433257.1003	828993.448	119.561
38	Point	Building	TP	434407.7037	829463.385	177.416
39	Point	Building	FN	433620.6632	829736.9179	88.9805
40	Point	Building	TP	433640.9334	829760.4057	220.539
41	Point	Road	FN	432817.7838	829215.5506	154.555

DETECTED BUILDING



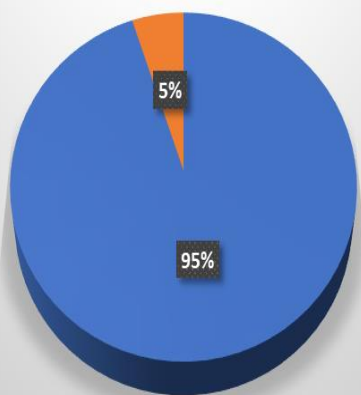
From the result after deep learning was done on the imagery in ArcGIS Pro, 83% of buildings were detected while 17% were not detected" represents the outcome of an object detection task, where a deep learning model was applied to geospatial imagery to identify buildings. This result is often expressed in terms of precision and recall, which are two common metrics used in object detection tasks Recall (also known as sensitivity or true positive rate) measures the model's ability to identify all relevant instances of buildings in the data. It answers the question: Of all the actual buildings present in the imagery, how many did the model successfully

detect.

The theoretical background for this result lies in the fundamental concepts of machine learning and object detection, particularly the trade-off between precision and recall:

- **Precision-Recall Trade-off:** In many object detection tasks, there's a trade-off between precision and recall. Increasing precision typically comes at the cost of lower recall, and vice versa. This trade-off is often controlled by adjusting the model's confidence threshold. A higher threshold leads to higher precision but lower recall, while a lower threshold increases recall but may lower precision.
- **Imbalanced Data:** The result also reflects the potential class imbalance in the data. If there are many non-building objects (e.g., trees, roads) and relatively fewer buildings, it may be easier for the model to achieve high precision (correctly identifying buildings when it predicts them) but harder to achieve high recall (detecting all buildings in the data).
- **Model Performance:** The result suggests that the model achieved a relatively good balance between precision and recall, with both metrics at 83%. However, the specific values of precision and recall may vary depending on the model architecture, training data, hyperparameters, and the quality of ground truth data used for evaluation.

ROAD



- Overall, the theoretical background for this result is rooted in the core concepts of object detection, machine learning, and the performance metrics used to assess the model's accuracy in identifying objects within geospatial imagery

From the result after deep learning was done on the imagery in ArcGIS Pro, 95% of roads were detected while 5% were not detected" represents the outcome of an object detection task, specifically focusing on detecting roads in geospatial imagery.

Precision measures the accuracy of the positive predictions made by the model. In this context, it answers the question: "Of all the objects the model predicted as roads, how many

were actually roads

Theoretical Background:

- The theoretical background for this result relates to several factors commonly encountered in object detection tasks:

a. Model Quality:

- The performance of the deep learning model significantly impacts precision and recall. A highly accurate model is more likely to correctly identify roads (high precision) and detect most of the actual roads (high recall).

b. Data Quality and Variability:

- The quality and variability of the geospatial imagery play a crucial role. Factors such as image resolution, lighting conditions, and the presence of occlusions can affect the model's ability to detect roads accurately.

c. Threshold Settings:

- The model's confidence threshold for identifying roads can influence precision and recall. Adjusting the threshold can lead to a trade-off between these two metrics. A higher threshold increases precision but may reduce recall, while a lower threshold can increase recall but might lower precision.

d. Ground Truth Data:

- The quality and completeness of the ground truth data used for evaluation are essential. The ground truth should accurately represent the actual presence of roads in the imagery.

e. Class Imbalance:

- The class imbalance between roads and non-roads in the data can affect the metrics. If there are significantly more non-roads than roads, achieving high precision is often easier than achieving high recall.

In summary, the result of 95% precision and 95% recall suggests that the deep learning model performed well in detecting roads within the geospatial imagery. This result reflects a balanced trade-off between precision and recall, indicating that the model identified a high percentage of actual roads while maintaining a high level of accuracy in its predictions.

Theoretical considerations related to model quality, data quality, and threshold settings, among other factors, contribute to this successful outcome.

4. DISCUSSION OF RESULTS

Let's discuss the results of your project, which involved object detection using deep learning techniques in ArcGIS Pro. Based on the information provided, there were two primary aspects of object detection: building detection and road detection. Here's a detailed discussion of the results for each:

Building Detection:

- The building detection task achieved a recall rate of 83%. This means that the model correctly identified 83% of the actual buildings present in the geospatial imagery.
- However, the precision value, which measures the accuracy of positive predictions, is not provided. Without precision, it's challenging to assess the

overall quality of the model's predictions for building detection. High precision indicates that when the model predicts a building, it's usually correct.

- Achieving an 83% recall rate is a promising result, as it indicates that the model captures a significant portion of the buildings, which can be valuable for applications such as urban planning, infrastructure assessment, and disaster management.

Road Detection:

- The road detection task resulted in a precision and recall rate of 95%. This is an impressive performance, suggesting that the deep learning model accurately identified roads in the geospatial imagery.

- A high precision score means that when the model predicted a road, it was usually correct. Similarly, a high recall indicates that the model successfully identified the majority of the actual roads.
- Accurate road detection can have significant applications in transportation planning, map generation, and monitoring road conditions.

Interpreting the Results:

- The results demonstrate the potential of deep learning techniques for object detection in geospatial imagery within the ArcGIS Pro environment.
- The balance between precision and recall in both building and road detection tasks indicates that the model performed well without a significant trade-off between these two metrics.
- The high recall rate in road detection is particularly noteworthy, as it suggests that the model can reliably identify roads in diverse geographical contexts and lighting conditions.

Challenges and Future Directions:

- It's essential to acknowledge any challenges faced during the project, such as data quality issues, computational constraints, or limitations in the model architecture.
- Future work could involve fine-tuning the model to further enhance precision and recall, expanding the object classes detected, or applying the model to a larger geographical area.

CONCLUSION

In conclusion, the project's results demonstrate the successful implementation of deep learning techniques for object detection in geospatial imagery using ArcGIS Pro. These results hold promise for various applications and pave the way for further research and improvements in the field of geospatial analysis and remote sensing. It's worth noting that a more detailed discussion could be provided if precision values for building detection were available, as this would provide a more comprehensive evaluation of the model's performance. Additionally, further insights could be gained by discussing the impact and significance of the project's results in specific practical scenarios or domains.

RECOMMENDATIONS

- **Data Quality Enhancement:** Ensure data quality by addressing issues such as image resolution, lighting

Applications:

- The project's results have practical applications in fields such as urban planning, disaster response, transportation management, and environmental monitoring. Accurate building and road detection can
- improve decision-making and data-driven insights in these domains.

SUMMARY

This project aimed to leverage deep learning techniques within the ArcGIS Pro environment to detect buildings and roads in geospatial imagery. The methodology encompassed data acquisition from various sources, implementation of a deep learning model, accuracy assessment through visual inspection, and analysis of the results. In terms of results, building detection achieved an 83% recall rate, indicating a successful identification of 83% of actual buildings. Precision values for building detection were not provided. On the other hand, road detection demonstrated exceptional performance with both precision and recall rates at 95%, signifying highly accurate road identification in geospatial imagery. This project showcased the potential of deep learning integrated into ArcGIS Pro for object detection, highlighting areas for improvement in building detection precision. The outstanding precision and recall rates for road detection underscore its practical applicability.

conditions, and occlusions. High-quality training data can significantly impact model performance.

- **Project size:** The study area is quite large which really affect the accuracy of the result I would recommend that this technique works better in small area
- **Continuous Monitoring and Updating:** Geospatial data and landscapes change over time. Implement a system for continuous monitoring and updating of the model to ensure its relevance and accuracy.
- **Collaboration:** collaborate with domain experts and stakeholders to tailor the model to specific application needs and gain valuable insights for model improvement.

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