



ENTITY AND OBJECT DETECTION WITH PRECISION IN SATELLITE IMAGERY

K. Santhoshi Rupa¹, K. Harshitha Mahalaxmi², K. Harshita³, K. Sushma Grace⁴, M. Keerthi⁵

1,2,3,4,5 Department of Computer Science and Engineering, Vignan's Institute of Engineering for Women, Visakhapatnam, Andhra Pradesh, India

ABSTRACT

This paper shifts focus from the traditional CNN methods to the innovative YOLO architecture for automated object detection in high-definition satellite images. Through the incorporation of satellite metadata, our approach achieves exceptional performance, overcoming the limitations of manual object identification. Extensive testing validates our method's heightened accuracy in object detection tasks. This research marks a significant stride in the field of satellite image analysis, providing valuable applications in urban planning, environmental surveillance, and disaster response. Leveraging the capabilities of deep neural networks and YOLO, our system delivers reliable and efficient detection results. Comparative studies emphasize the superiority of our system over traditional approaches. Our methodology contributes to the progression of satellite image analysis, offering practical and effective solutions for a range of real-world applications. By integrating deep learning techniques with satellite metadata, our system ensures precise and consistent object detection. The YOLO-based approach stands out as a robust solution for remote sensing applications requiring high-precision detection.

Keywords: Object Detection, Satellite Imagery, YOLOv8, Deep Learning

INTRODUCTION

In the current landscape of satellite technology, the availability of high-definition satellite imagery has transformed numerous sectors, including urban planning, environmental oversight, and disaster response. While the wealth of satellite data offers unprecedented opportunities, it also poses significant challenges, particularly in the efficient and accurate processing of these extensive datasets.

Object detection within satellite images holds the key to extracting crucial insights and practical information. However, traditional manual analysis methods are time-intensive, require substantial labor, and are susceptible to errors. To overcome these obstacles, the integration of deep learning methods presents a viable solution by automating the identification and classification of objects in satellite imagery.

In this study, we introduce an innovative approach to object detection in satellite images by harnessing the capabilities of deep learning, specifically utilizing the YOLOv8 model. YOLO (You Only Look Once) stands as a cutting-edge object detection algorithm renowned for its rapid processing and precision. Our approach entails the design and training of a YOLOv8 model customized to identify specific objects within satellite imagery.

LITERATURE SURVEY

Adekanmi Adeyinka Adegun¹ Jean Vincent Fonou Dombou², Serestina Viriri¹, John Odindi³, "State-of-the-Art Deep Learning Methods for Objects Detection in Remote Sensing Satellite Images" [1]:

Object detection in satellite images plays a crucial role in various sectors like environmental monitoring, disaster prevention, urban planning, and socio-economic services. Despite the growing interest in using deep learning techniques for this task, their performance can be hindered by factors

such as complex landscapes, similarities between different classes of objects, and challenges in obtaining diverse and representative training data.

To overcome these obstacles, this research leverages multi-object detection deep learning algorithms coupled with transfer learning on satellite imagery from a diverse landscape. The study utilizes a unique dataset featuring five different object classes, sourced from Google Earth Engine and covering various locations in southern KwaZulu-Natal province, South Africa. The images in this dataset exhibit a range of object sizes and resolutions. Mark Pritt¹, Gary Chern², IEEE, "Satellite Image Classification with Deep Learning" [2]:

Satellite images play a crucial role in disaster response, law enforcement, and environmental oversight. Due to the vast areas these images cover and limited manpower available, there's a pressing need for automation. Traditional methods often struggle with accuracy and reliability in object detection and classification tasks. Deep learning, a machine learning subset, offers promising avenues for automation. Specifically, convolutional neural networks (CNNs) have excelled in image analysis tasks. In our research, we harness these capabilities to identify objects and facilities in high-resolution, multi-spectral satellite images. We focus on categorizing objects using the IARPA Functional Map of the World (fMoW) dataset, which includes 63 distinct classes. Our system is built on an ensemble of CNNs and incorporates additional neural networks that blend satellite metadata with image features to improve classification. Developed in Python, using Keras and TensorFlow, the system runs on a Linux server with an NVIDIA Titan X graphics card.

Kazuki Uehara, Hirokazu Nosato, Masahiro Murakawa, and Hidenori Sakanashi, IEEE "Object Detection in Satellite Images Based on Active Learning Utilizing Visual Explanation" [3]:

CNNs are gaining traction in object detection within satellite imagery. However, obtaining labeled datasets for training CNNs in the remote sensing domain is a challenging and time-intensive task, leading to a shortage of

adequately labeled data. To tackle this issue, we employ an active learning (AL) method to train CNNs using a limited set of labeled samples. AL optimizes the training dataset by selecting the most informative samples for human labeling, aiming to enhance the learning process. An effective query strategy is crucial for AL, as it significantly impacts the CNN's learning capability. In our approach, we introduce a specialized query strategy tailored for efficient CNN training. This strategy prioritizes samples based on the discrepancy between the classifier's predictions and the visual explanations, which highlight the class-specific details within the image's feature maps. Our experiments confirm the effectiveness of our strategy. A CNN trained using our method required 95% fewer training samples, yet maintained a 94% detection accuracy compared to a fully labeled dataset-trained CNN. Additionally, our strategy reduced the training sample requirement by 30% compared to traditional methods while achieving comparable performance.

Hiroki Miyamoto, Kazuki Uehara¹, Masahiro Murakawa¹ Hidenori Sakanashi, Hirokazu Nosato, Toru Kouyama¹, Ryosuke Nakamura¹ IEEE, "Object Detection in Satellite Imagery Using 2-Step Convolutional Neural Network" [4]:

This study introduces a new approach to object detection in satellite images. We developed a dual convolutional neural network (CNN) system designed to optimize both precision and recall. To validate our approach, we used golf courses as the target objects. Our deep learning method surpassed the accuracy of existing object detection techniques.

EXISTING METHOD

In the Existing systems for object detection within satellite imagery, Convolutional Neural Networks (CNNs) serve as the primary technology for automated object identification in images. The process initiates with a vast dataset of satellite images, each annotated with labels that specify the objects present and their respective categories. These annotated images form the training data for the CNN model, allowing it to learn and discern complex patterns and characteristics associated with various objects. As the CNN undergoes training, it fine-tunes its internal parameters through iterative adjustments to reduce the discrepancy between its predictions and the actual object labels. This

iterative learning process enhances the CNN's capability to accurately identify objects. Upon successful training, the CNN model gains the proficiency to autonomously analyze new satellite images, accurately determining the presence and types of objects based on the patterns and features it has learned.

PROPOSED METHOD

Our proposed system leverages the YOLOv8 (You Only Look Once) algorithm to enhance object detection in satellite imagery. YOLOv8 is a state-of-the-art deep learning technique known for its efficiency and accuracy in detecting objects within images. In our system, YOLOv8 is employed to automatically identify objects present in satellite images, even when multiple objects are overlapped or densely packed.

The process begins by inputting a satellite image into the YOLOv8 model. The model then analyzes the entire image in a single pass, dividing it into a grid and predicting bounding boxes around objects along with their corresponding class names. This approach allows for real-time object detection with high accuracy, as the model considers contextual information and spatial relationships between objects within the image.

Once the objects are detected, bounding boxes are drawn around them to visually highlight their locations within the satellite image. Additionally, each detected object is labeled with its respective class name, providing valuable information about the type of object identified (e.g., building, vehicle, vegetation). This facilitates easy interpretation and analysis of the detected objects by users.

By employing YOLOv8 for object detection, our proposed system offers several advantages, including improved efficiency, accuracy, and scalability compared to traditional methods. The ability to detect objects with bounding boxes and class labels enhances the interpretability of the results, making it suitable for various applications such as urban planning, environmental monitoring, and disaster response. Overall, our system provides a robust and user-friendly solution for object detection in satellite imagery, empowering users to extract valuable insights from satellite data with ease.

DESIGN STRUCTURE

The satellite image detection project is structured around several core modules to deliver a seamless and efficient user experience.

User Interface (UI):

At the forefront is the User Interface, offering a user-friendly web platform. It features an image upload section for users to submit their satellite images and a dedicated page to display the detection results.

Preprocessing Module:

Once images are uploaded, the Preprocessing Module springs into action. This module readies the images for analysis by performing necessary adjustments. It may resize images for uniformity, normalize brightness and contrast, or apply other transformations to ensure consistent image quality, setting the stage for accurate detection.

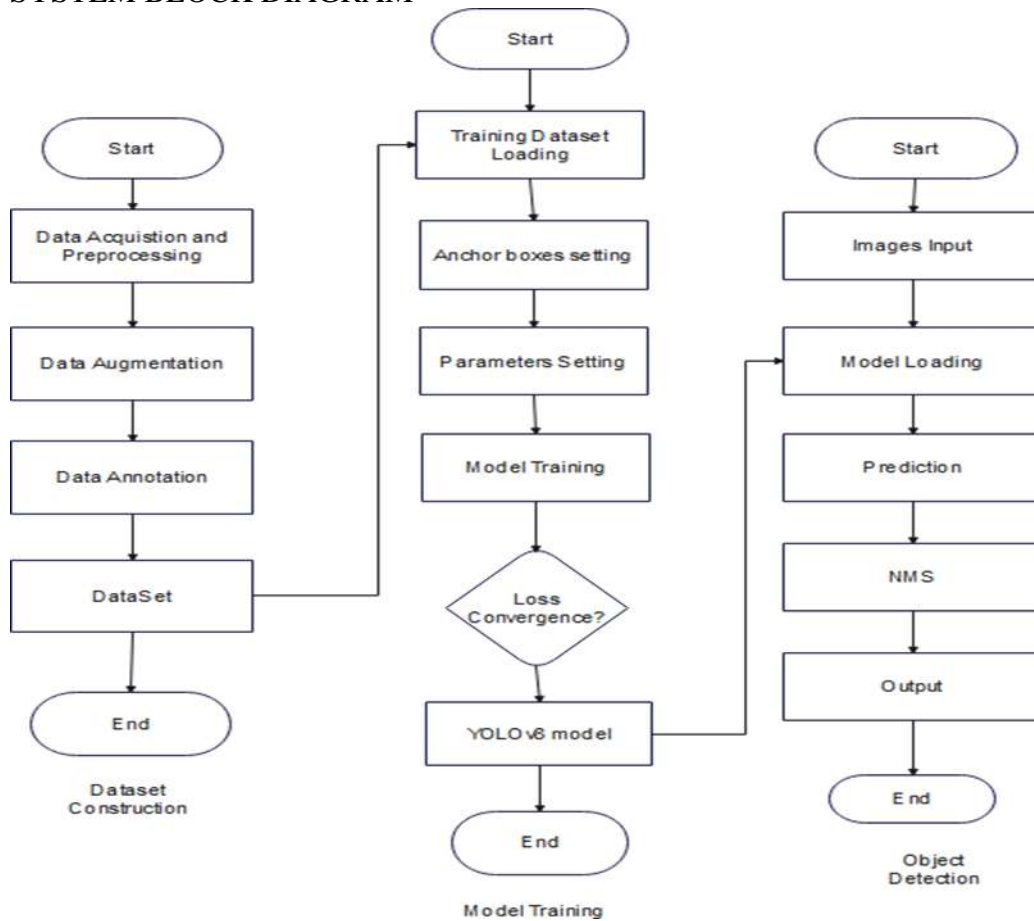
Object Detection Module:

Central to the system is the Object Detection Module. It harnesses the power of a pre-trained YOLOv8 model to execute object detection tasks. This model scrutinizes the images to pinpoint objects like buildings, vehicles, or infrastructure. The advanced algorithms of YOLOv8 allow for swift and precise detection across the entire image, ensuring both speed and accuracy.

Annotation and Visualization Module:

After detecting objects, the Annotation and Visualization Module comes into play. It enhances the images by overlaying bounding boxes or labels on the detected objects. Moreover, it optimizes these annotated images for clear display on the results page. These refined images are saved with unique identifiers, making it easy to differentiate and retrieve them.

SYSTEM BLOCK DIAGRAM



RESULT ANALYSIS

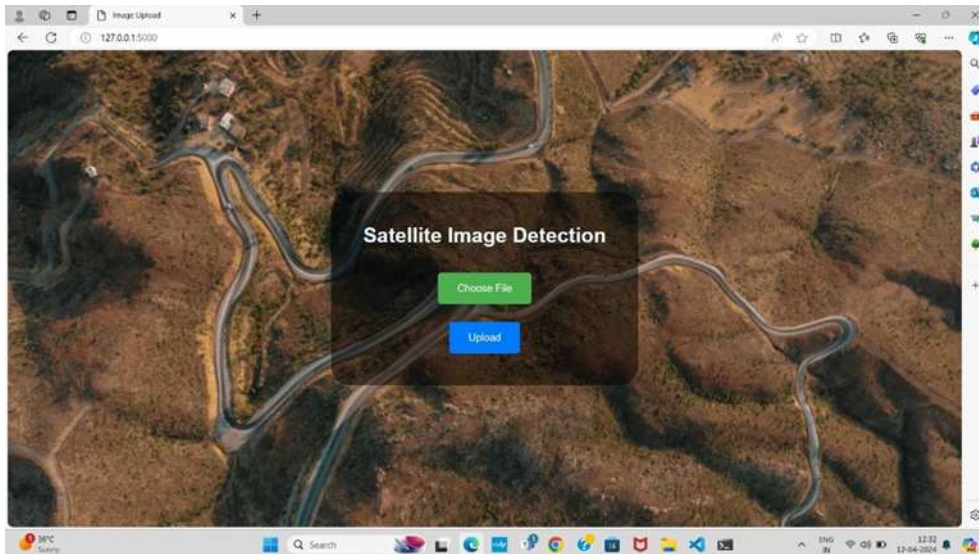


Figure 1: Input the image

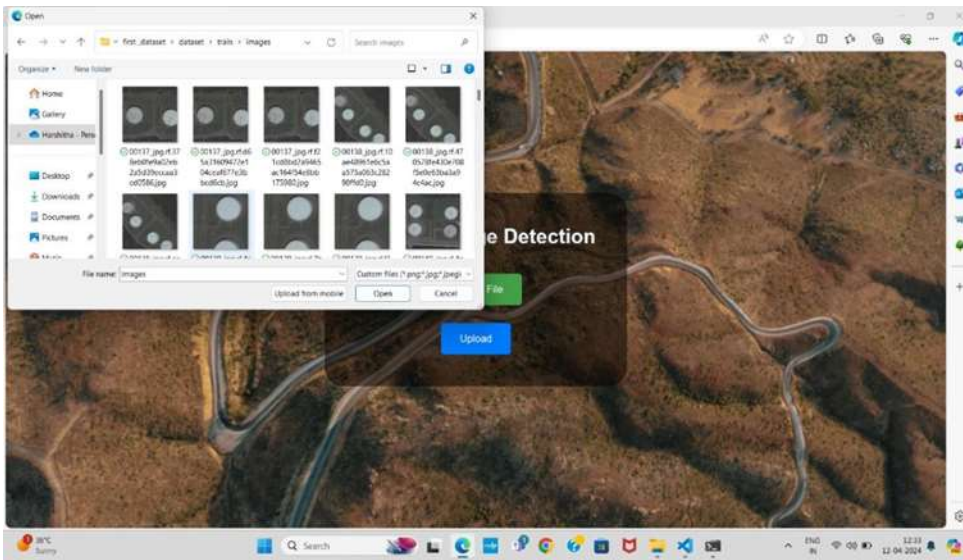


Figure 2: Upload the Satellite Image



Figure 3: Detect the Objects in Satellite image

CONCLUSION

In Conclusion, our project marks a significant breakthrough in spotting objects within satellite images. By using advanced techniques like YOLOv8 and deep learning, we've built a powerful system that can automatically detect objects with incredible accuracy. This means we can quickly identify things like buildings, vehicles, or natural features from satellite pictures. Plus, with our user-friendly web application, anyone can easily upload an image and see the results in real-time. Our project not only showcases the potential of technology in analyzing satellite images but also makes it accessible to everyone. With further improvements, our system could have a profound impact on various fields, from urban planning to disaster response.

REFERENCES

- 1) Weijia Li, Haohuan Fu, Le Yu, and Arthur Cracknell," Deep Learning Based Oil Palm Tree Detection and Counting for High-Resolution Remote Sensing Images," in MDPI Remote Sens, 2017,9,22

- 2) Gang Chen, Geoffrey J. Hay, Luis M. T. Carvalho, and Michael A. Wulder, "Object-based change detection," *International Journal of Remote Sensing*, vol. 33, pp. 4434–4457, 2012, doi:10.1080/01431161.2011.648285.
- 3) Tomohiro Ishii, Edgar Simo-Serra, Satoshi Iizuka, Yoshihiko Mochizuki, Akihiro Sugimoto, Hiroshi Ishikawa, and Ryosuke Nakamura, "Detection by classification of buildings in multispectral satellite imagery," in *International Conference on Pattern Recognition (ICPR)*, 2016, doi:10.1109/ICPR.2016.7900150
- 4) J. Redmon and A. Farhadi, "YOLOv3: An Incremental Improvement," 8 April 2018. [Online]. Available: arXiv:1804.02767 [cs.CV]
- 5) Jiao, L.; Zhang, F.; Liu, F.; Yang, S.; Li, L.; Feng, Z.; Qu, R. A survey of deep learning-based object detection. *IEEE Access* 2019, 7, 128837–128868.
- 6) Bochkovskiy, A.; Wang, C.Y.; Liao, H.Y.M. Yolov4: Optimal speed and accuracy of object detection. arXiv 2020, arXiv:2004.10934.
- 7) Saito, S.; Yamashita, T.; Aoki, Y. Multiple object extraction from aerial imagery with convolutional neural networks. *Electron. Imaging* 2016, 2016, 010402-1–010402-9.
- 8) Chang, R.-I.; Ting, C.; Wu, S.; Yin, P. Context-Dependent Object Proposal and Recognition. *Symmetry* 2020, 12, 1619.