Wind Sight: Precision Windmill Detection Using Satellite Images with U-net Model

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Abstract—**The rising development of renewable energy infrastructure, particularly wind farms, calls for effective monitoring and management solutions. This research explores the use of deep learning, specifically convolutional neural networks (CNN) and semantic segmentation models, to detect windmills in satellite imagery. Leveraging high- resolution satellite imagery and the U-Net architecture, this study emphasizes precise identification and localization of windmills. The methodology includes collecting and annotating a windmill satellite image dataset, followed by data preprocessing to improve image quality and generate binary masks. This dataset trains the U-Net model, which successfully segments windmills from test images with a validation accuracy of 93.7%. This research demonstrates the effective combination of deep learning and geospatial analysis, presenting a scalable approach for wind energy resource monitoring.**

Index Terms—**windmill, images, QGIS, Annotations, CNN, Tensorflow, keras, augmentations, satellite imagery)**

I. INTRODUCTION

As the world increasingly shifts toward renewable energy sources, the monitoring and assessment of windmill deployment has become crucial for governments, energy companies, and researchers alike. Traditional detection methods, which often rely on manual inspections and ground surveys, can be both costly and time-consuming. In contrast, automated systems that utilize satellite imagery and deep learning models present a promising solution for enhancing the accuracy and efficiency of windmill detection and monitoring. This study goals to develop a deep learning-based approach for the precise identification of windmills in satellite images. We specifically investigate the effectiveness of convolutional neural network (CNN)-based object detection models and semantic segmentation techniques, such as U-Net, to achieve high-precision windmill detection. A dataset of satellite imagery has been collected and processed to facilitate the training and validation of the U-Net model. Our ultimate research presents a comprehensive evaluation of the aforementioned deep learning techniques, focusing on their performance, challenges, and real-world applications. By demonstrating the synergy between high-resolution satellite imaging and deep learning algorithms, our aim to enhance the accuracy and accessibility of windmill identification, thereby contributing to the effective management of renewable energy resources.

II. LITERATURE SURVEY

N. Laban et. al [1] discussed Object detection in satellite imagery has advanced with the increase of deep learning, particularly Convolutional Neural Networks (CNNs). Satellite images present challenges due to varying object sizes, complex backgrounds, and dense scenes. Two main detection methods have been explored: two-stage approaches like region-based Convolutional Neural Networks (R-CNN), which generate region proposals before classification, and one-stage methods like YOLO and SSD, which detect objects in a single step. YOLOv3 stands out for its speed and ability to detect objects at multiple scales, making it highly effective for satellite images. One of the key challenges in satellite imagery is detecting small objects, which are often underrepresented in pixel size. To address this, dilated anchors have been proposed to expand bounding boxes, improving accuracy by covering both objects and surrounding areas. Data augmentation techniques, such as scaling,

rotation, and color adjustments, further enhance model performance by increasing data diversity. Adjusting anchor sizes and refining model architectures have been shown to improve metrics like precision, recall, and mean Average Precision (mAP), particularly for small object detection.

R. R. Subramanian et. al [2] discussed Object detection and counting in satellite imagery are crucial for several applications such as urban planning, agriculture, and environmental monitoring. These tasks have been enhanced by deep learning models like Convolutional Neural Networks (CNNs). Automated object counting, compared to manual methods, offers improved efficiency and accuracy. Several studies have explored different models for satellite image detection. In 2021, a framework used down-sampled images to detect airports and neighboring objects using the DCR-CNN algorithm. Another study in 2022 tackled the challenge of limited datasets with the RetinaNet model, achieving 90% accuracy using the TripleSAT and DOTA datasets. Models like YOLOv3 and YOLOv4 have also been applied to aerial images, achieving strong results despite challenges like high spatial and spectral resolution. Self-supervised learning (SSL) techniques have further improved detection by pre-training
models on large unlabeled datasets, later fine-tuned for object counting tasks. Lightweight models like Mixed YOLOv3-LITE enhance real-time detection on embedded devices. Performance metrics such as accuracy, precision, and recall have been used to evaluate models, with image augmentation and hyperparameter tuning boosting performance. Overall, deep learning-based approaches are effective for object detection and counting in satellite imagery.

W. Zhang et. al [3] discussed Detecting windmills using satellite imagery has advanced significantly from traditional methods like SVM, which faced limitations with high-resolution images. Recent developments in deep learning, particularly Convolutional Neural Networks (CNNs) and U-Net, have improved detection accuracy for small objects like windmills. Studies like those of Mridula and Sharma (2021) and Bentes et al. (2018) have shown CNNs' effectiveness in both optical and SAR images, outperforming older methods. Mid-resolution satellite data from Sentinel-2, as explored by Tertre and

Laurençot (2022), offers global applicability, although detecting windmills with only a few pixels is challenging. Using the U-Net framework, which combines spatial and semantic information, their study achieved an F1 score of 0.95 for windmill detection. The introduction of transfer learning using pre-trained networks like VGG16 and ResNet50 further enhanced detection across different countries. Fine-tuning models trained on one region for another improved cross-region accuracy. Although challenges like dataset inconsistencies and resolution limitations remain, deep learning techniques show promise in improving windmill detection accuracy on a global scale.

N. Mandroux et. al [4] Wind turbine detection from satellite imagery is essential for energy management and planning. Sentinel-2, launched by the European Space Agency, provides freely available mid-resolution images that can be used for large-scale wind turbine monitoring. Traditional detection methods, such as neural networks, require high-resolution images and large annotated datasets, which are often costly and difficult to obtain. In response, Mandroux et al. (2021) introduced a computationally efficient method based on the a contrario framework. This approach uses the geometric features of wind turbines, particularly their shadows and bright hubs, to detect turbines in Sentinel-2 images. The algorithm calculates the turbine's shadow and hub positions using the known satellite and sun angles along with the height of the turbine tower. This allows for wind turbine detection with lower computational costs. The method showed improved detection rates compared to prior models like Chen et al. (2018), particularly in low-resolution images. However, further improvements are needed for more accurate mass detection. Future research aims to incorporate SAR data and explore new techniques for detecting entire wind farms.

S. Godbole and G. Phadke [5] discussed Edge detection has become crucial in satellite image processing for applications such as coastline mapping and cyclone tracking. Traditional edge detection methods like Sobel, Roberts, Prewitt, Canny, and Laplacian of Gaussian are widely used but face challenges with noise and accuracy. These classical methods use gradient or zero-crossing techniques to

detect edges but often produce less clear results in complex environments. A newer approach, the fractional order derivative method, offers improved performance, particularly in terms of Peak Signal-to-Noise Ratio (PSNR) and Mean Square Error (MSE). This method generalizes traditional gradient operators, allowing for more precise edge detection in noisy images. Studies show that the fractional order method outperforms classical techniques, especially in eliminating irrelevant noise while maintaining necessary details, making it particularly useful in real-time applications like cyclone imagery analysis. It also reduces computational complexity, making it an efficient choice for satellite image edge detection. While classical algorithms remain relevant, the fractional order method presents a more balanced solution for modern challenges, and future research should further enhance its capabilities.

D. Chen et. al [6] discussed Object detection in remote sensing has advanced significantly with the rise of satellite imaging, especially for detecting wind turbines, which are crucial for sustainable energy management. Traditional methods, for example Principal Component Analysis (PCA), Histograms of Oriented Gradients (HOG), and Local Binary Patterns (LBP), were effective but limited due to manual feature

extraction, making them less adaptable to complex satellite images. Recent developments in deep learning, particularly Convolutional Neural Networks (CNNs), have revolutionized detection. Among these, YOLO (You Only Look Once) stands out for its real-time detection capabilities, outperforming traditional models in speed and efficiency. The study "Research on Fast Detection Method of Wind Turbine in Remote Sensing Image Land Area Based on YOLO" presents a robust detection framework integrating land use data, wind speed, and slope with YOLO v5x, achieving a recall rate of 94.87% and accuracy of 82.04%. By incorporating data augmentation techniques, the model improved generalization. This deep learning-based approach marks a significant advancement in detection speed and accuracy, making it suitable for large-scale remote sensing applications, with potential for further global use. Gatkine, Sakshi, Imran, Ahmad, et al. (2023) [18] in Teacher Management System web app is developed to manage teaching related task by using web technologies.

Gupta, Narayani, Imran, Ahmad, et al. (2023) [19] In this Object Detection using YOLO-I-Sight is used to detection the object by using YOLO.
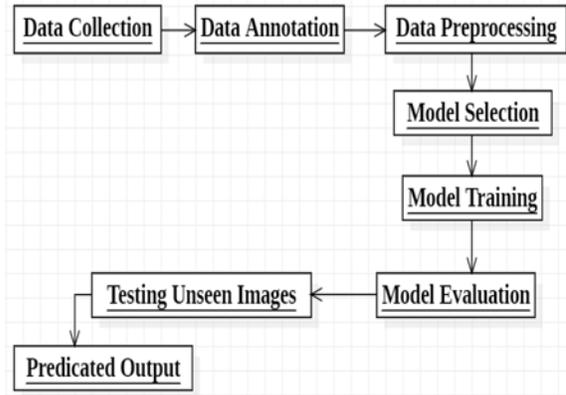
III. METHODOLOGY

Figure 3.1 Work flow Diagram

The work flow diagram illustrates a process, starting from data collection, annotation, and preprocessing, followed by model selection, training, evaluation, and testing on unseen images to produce the final prediction.

This research focuses on detecting windmills in satellite images using the U-Net model architecture, which is specifically designed for image segmentation tasks. Windmills are essential for sustainable energy production, making detection vital for maintenance and planning purposes. By utilizing satellite imagery, we aim to create a robust dataset for training and validating our model. The project, titled "Wind Sight: Precision Windmill Detection Using Satellite Images with Deep Learning Models," integrates deep learning techniques to enhance the detection process.

To facilitate the detection process, we employed a variety of tools and technologies that streamline image processing and model training. TensorFlow and Keras were utilized to construct and train the U-Net model, providing a flexible framework for developing deep learning applications. OpenCV played a critical role in image manipulation and post-processing, ensuring the imagery was prepared for analysis. Furthermore, Albumentations was implemented for data augmentation, expanding the dataset and enhancing the model's capability to generalize across various conditions.

In addition to these tools, Pillow was used for efficient image handling, while Matplotlib enabled effective visualization of model performance through various metrics and plots. For annotating satellite images and creating bounding boxes around the detected windmills, QGIS was employed, converting these annotations into binary masks suitable for training the model. Access to satellite imagery was obtained through the Overpass Turbo API and Google Maps Satellite, forming the foundation of our dataset.

1.1) Data Collection and Annotations

Figure 3.1.1 dataset creation using the Overpass Turbo API along with Google Maps satellite

The dataset for this project was collected using the Overpass Turbo API along with Google Maps satellite web applications.
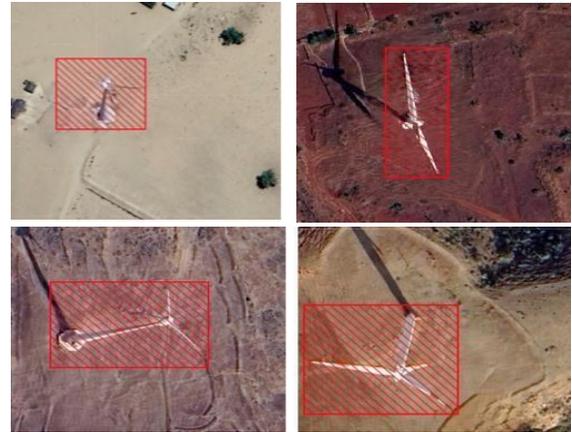

Figure 3.1.2 Annotations on windmill in images by using the QGIS tool

The images obtained were then processed and annotated with the help of QGIS tool, which allowed for the creation of bounding boxes around the windmills in the images. Initially, the dataset consisted of 420 images, providing a solid foundation for the analysis.

1.2) Data Preprocessing

To maintain uniformity, all images were resized to a standard dimension of 512x512 pixels. Additionally, normalization was applied to scale the pixel values between 0 and 1, which helps improve the efficiency of the model during training. To enhance the dataset's robustness, a variety of augmentation techniques were implemented, including horizontal and vertical flips, random rotations, and scaling.

Figure 3.2.1 augmented images

Image augmentation involves applying techniques like

rotation, flipping, and brightness changes to increase dataset diversity. These transformations improve model accuracy by helping it generalize to new data, making it more robust in recognizing windmills from various angles and conditions in satellite images.
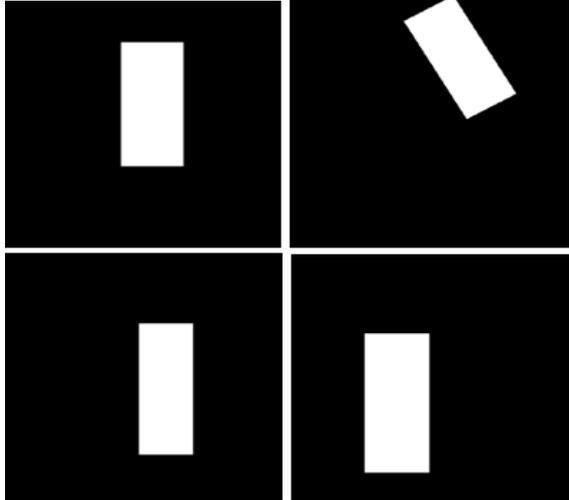

Figure 3.2.2 Augmented masks of images

The images represent binary masks used for windmill detection, where the windmills are highlighted against the background. These masks assist in training models by clearly defining the regions of interest, enabling accurate detection and localization of windmills in satellite images during the training process.

Once the augmentation was complete, the dataset was partitioned into training and validation sets, consisting of 2,268 images for training and 252 for validation. This allocation enables the model to learn effectively while ensuring it generalizes well to new data. Quality assurance checks were performed to verify the accuracy and integrity of both the images and their annotations, resulting in a balanced dataset that adequately represents both classes. The final dataset includes 2,520 images, forming a solid foundation for the model's training process.

1.3) Model Definition

In this study, we developed a U-Net model using TensorFlow and Keras specifically designed for detecting windmills in satellite images. The model processes input images of size 512x512 pixels, effectively handling standard RGB images. The architecture comprises a contracting path that captures features through successive convolutional layers with ReLU activation, followed by max-pooling layers that decrease spatial dimensions. At the bottleneck, two convolutional layers with 1024 filters extract high-level features.

The expansive path employs transposed convolutions for upsampling, integrating features from corresponding encoder layers via concatenation to preserve spatial details. The final layer consists of a 1x1 convolution with a sigmoid activation function, generating a binary mask indicating the presence of windmills. The model is compiled with the Adam optimizer and binary cross-entropy loss function, utilizing the Mean Intersection over Union (MeanIoU) metric for segmentation performance assessment. This architecture is optimized for effective training and accurate segmentation of windmill locations within satellite imagery.

1.4) Model training

The training of the model was conducted using several strategic callbacks to enhance its performance and ensure efficient learning. We implemented ReduceLROnPlateau to modify the learning rate when the validation loss plateaued, reducing it by a factor of 0.2 if no improvement was observed over a span of 5 epochs. This approach aids in fine-tuning the training process for better convergence. To ensure that we retained the most effective model during training, we utilized ModelCheckpoint, which saves the model only when there is an improvement in the validation loss. Additionally, we applied EarlyStopping to terminate the training process if the validation loss unsuccessful to increase for 10 consecutive epochs, thereby preventing overfitting and unnecessary computations. The model was trained over 20 epochs with a batch size of 10, using specified training and validation datasets. This comprehensive training strategy allowed the model to learn effectively while maintaining optimal performance throughout the training process.

1.5) Model Evaluation

After training the model, we conducted an evaluation to assess its performance on the validation dataset. The U-Net model, previously saved during training, was loaded for this purpose. We employed the evaluate function to obtain the validation loss and accuracy, which serve as critical indicators of the model's ability

to generalize to new, unseen data. The evaluation results were then displayed, providing a clear summary of the model's effectiveness in detecting windmills. This assessment allowed us to understand the strengths of the model and pinpoint areas that might require further refinement in future training cycles.

IV. RESULT AND DISCUSSION

The U-Net model showcased significant capabilities in identifying windmills within satellite imagery, achieving an impressive validation accuracy of 93.7%. This level of accuracy underscores the model's proficiency in distinguishing between images containing windmills and those that do not. To further assess the model's performance, several evaluation metrics were employed, including precision, recall, and F1-score, all of which contribute to a comprehensive understanding of the model's reliability. Various graphical representations were created to visualize the results, illustrating the performance metrics throughout the validation process. Furthermore, the evaluation on previously unseen images provided additional insights into the model's generalization abilities, demonstrating its effectiveness in accurately segmenting windmills across varying conditions. Visual outputs confirmed the model's capacity to delineate the structures of the windmills.
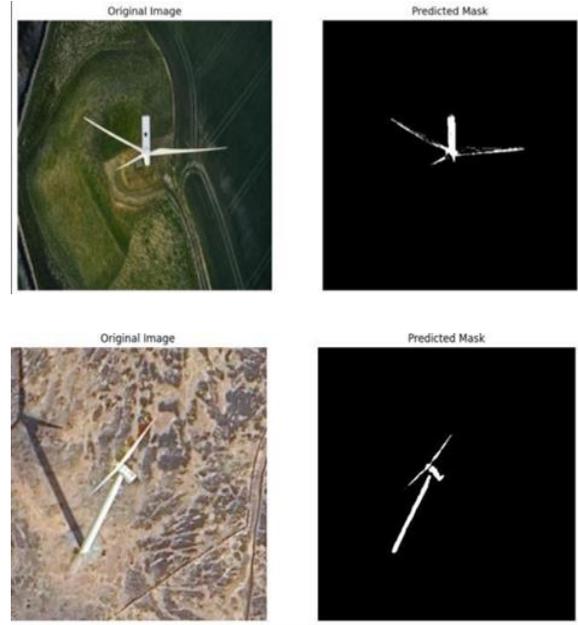

Figure 3.5.1 Testing a new unseen images

The images illustrate the model's performance when tested on unseen satellite images, where predicted masks highlight the windmill structures. This step assesses the model's generalization capabilities, validating its effectiveness in detecting windmills in new, untrained data, making it applicable for real-world scenarios.
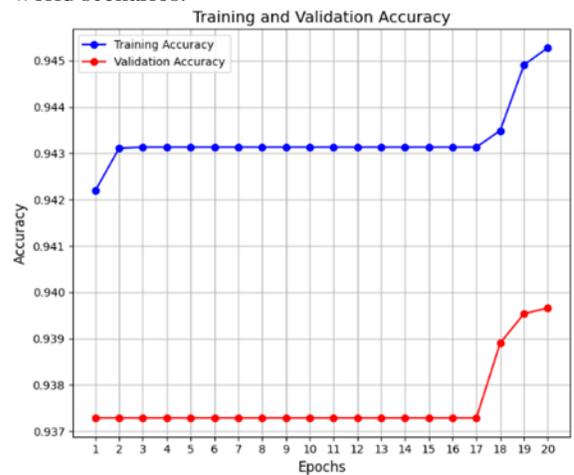

Figure 3.5.2 Displays the training and validation accuracy.

The presented graphs indicate stable performance across 20 epochs, with a steady increase in training accuracy and a notable improvement observed around epoch 17. Meanwhile, the validation accuracy remained consistently near 0.937, with slight

enhancements noted towards the conclusion of the training. The minimal difference between training and validation accuracy suggests effective generalization without indications of overfitting.
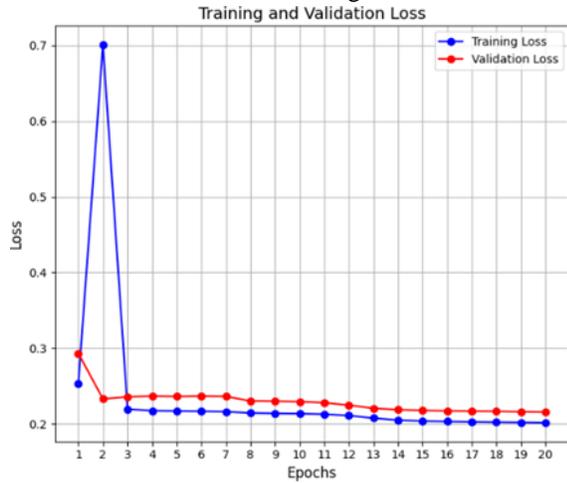

Figure 3.5.3 Outlines the training and validation loss

The loss graph indicates an initial spike in training loss at epoch 2, which quickly stabilized. Starting from epoch 3, both training and validation losses maintained low and closely aligned values, indicating that the model reached a balanced state in learning. The overall consistency in accuracy and loss trends emphasizes the model's dependability and its capacity to generalize effectively to new data.

V. DISCUSSION

The U-Net model demonstrated a validation accuracy of 93.7%, indicating its effectiveness in distinguishing between images that contain windmills and those that do not. However, when analyzing performance through metrics such as precision, recall, and F1-score, several concerns emerged. The precision rate was recorded at 19%, while the recall stood at 11%, leading to an F1-score of 14%. These metrics suggest that, despite the model's ability to classify a significant portion of the background correctly, it struggles considerably to identify windmills accurately. A notable finding is that the model frequently predicts backgrounds featuring grass and buildings, contributing to a high rate of false positives. This behavior can be linked to the class imbalance in the training dataset, where the sheer number of background pixels overshadows those representing windmills. Consequently, the model tends to default to

the predominant class, achieving a high accuracy while performing poorly in terms of precision and recall for the windmill class. Conversely, there are instances where the model successfully detects windmills without erroneously identifying the surrounding background. These cases indicate that when windmills are distinctly visible, the model can recognize them effectively, demonstrating its potential in situations where the turbines stand out against their environment. This dual behavior emphasizes the challenges faced in this detection task, as the model exhibits both the capability to accurately identify windmills and the tendency to confuse them with similar-looking background elements. To improve performance in detecting windmills relative to the background, adjustments to the prediction threshold were made. Lowering the threshold to 0.3 led to modest gains in recall (11%) but resulted in a decrease in precision (19%). This illustrates the inherent trade-offs involved in optimizing the model, highlighting the difficulty of enhancing detection rates for minority classes while managing the occurrence of false positives.

In conclusion, while the U-Net model presents potential as a viable tool for detecting windmills in satellite imagery, further enhancements are required to boost its sensitivity to windmill detection, particularly for real-world applications in renewable energy management. Ongoing efforts to mitigate class imbalance and consider additional strategies—such as using a more diverse training dataset or applying data augmentation techniques—may significantly improve the model's effectiveness in subsequent iterations. Figure 3.5.1 displays the testing of new unseen images, while Figure 3.5.2 and Figure 3.5.3 illustrate the training and validation accuracy and loss, respectively, reinforcing the observations made in this discussion.

VI. CONCLUSION

This study effectively developed a U-Net model for identifying windmills in satellite images, achieving an impressive validation accuracy of 93.7%. By leveraging high-resolution imagery, we expanded our original dataset of 420 images to a total of 2,520 meticulously annotated satellite images, which were processed and augmented to increase the model's

generalization over diverse environments. The utilization of deep learning methodologies, combined with tools like TensorFlow and Keras enabled efficient model training and validation.

However, despite its high accuracy, the model faced difficulties with precision and recall, largely due to class imbalance in the dataset. While it accurately classified background areas, it struggled to effectively detect windmills, leading to low F1-scores. This issue of misclassifying backgrounds highlights the necessity for further improvements in data collection and training approaches. The findings of this research have significant implications for renewable energy management, as precise windmill detection can greatly enhance strategic planning and maintenance activities. Future research should focus on mitigating class imbalance through improved data augmentation methods and incorporating more varied datasets.

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