Rooftop Detection, Size Estimation and Eco-friendly Infrastructure Planning Using Deep Learning

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Approval

APPROVAL

This thesis titled on "**Rooftop Detection, Size Estimation and Eco-friendly Infrastructure Planning Using Deep Learning**", submitted by **Asiful Haque(ID: 201-35-2961)** to the Department of Software Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of Bachelor of Science in Software Engineering and approval as to its style and contents.

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Declaration

I announce that I am rendering this study document under Md. Shohel Arman, Assistant Professor, Department of Software Engineering, Daffodil International University. I therefore state that this work or any portion of it was not proposed here therefore for Batchelor's degree or any graduation.

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Abstract

As worries about global warming, rising energy costs, and worsening air quality grow, this study investigates how deep learning models, specifically YOLOV5 and YOLOV8, can help with finding rooftops, estimating their sizes, and planning environmentally friendly infrastructure. The first part of the study talks about how important it is to find long-term answers to environmental problems, like installing solar panels on roofs and planting trees. Using drone footage and cutting-edge deep learning frameworks, the study carefully checks how well YOLOV5 and YOLOV8 work at different steps, such as collecting data, preprocessing it, adding to it, and choosing the best model. The results show that both models are good at finding rooftops. YOLOV5 has slightly better accuracy, recall, and mean average accuracy at the 50% Intersection over Union (IoU) threshold, while YOLOV8 is more stable across a wider range of IoU thresholds, as shown by its performance on the mAP50-95 metric. The results show that there are complex trade-offs between being accurate and being consistent. Overall YOLOV5 provides better accuracy in detecting and segmenting objects with 93% mAP(Mean Average Precision). They can help people who work with green energy, urban planning, and protecting the environment. This study helps us learn more about how deep learning can be used to solve important sustainability problems by showing us the pros and cons of YOLOV5 and YOLOV8 in the areas of rooftop recognition and planning eco-friendly infrastructure.

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Chapter 1

Introduction

The world faces pressing issues such as global warming, rising energy costs, and worsening air pollution. Non-renewable energy sources, such as burning fossil fuels and cutting down trees, have worsened these problems. To address these issues, more people are turning to green energy sources like solar power. Our study aims to detect the rooftop areas of urban areas to install renewable energy resources and green environment. It also explores the pros and cons of using rooftops in cities for solar panels and trees by detecting rooftop areas using deep learning. Drones will be used to capture high-quality images, and image processing and computer vision will be used to identify suitable rooftop locations. The part aims to demonstrate how combining solar energy with green infrastructure, such as trees, can help clean up the air and slow down global warming. The findings will benefit green energy professionals, policymakers, and urban planners, accelerating the process of making cities more resilient and sustainable.

The current part of the study will focus on finding rooftop areas from drone photos and figuring out how much room there is for installing solar panels and planting trees. We want to easily find and define rooftop areas by using image processing and computer vision methods. Beyond that, we will talk about the advantages of combining solar panels with green infrastructure, focusing on how trees can improve air quality and make solar panels work better and last longer. Additionally, we will talk about creative ways to increase the production of solar energy and lower its use, such as connecting solar photovoltaic panels to Battery Energy Storage Systems (BESS) and putting solar panels on water surfaces. Additionally, we will look at the potential of microgrid systems and how they can help lower power use. By the end of this section, we will have presented a thorough examination of the potential and long-term viability of green infrastructure and rooftop solar setups in cities.

Background

Issues over global warming, rising energy consumption, and declining air quality have grown in recent years [1]. As the world has been using non-renewable traditional energy sources for many years, this has been the main cause of serious global warming, which affects the entire planet. With CO_2 and CH_4 levels growing by 36% and 148% since 1750, respectively, human activity since the Industrial Revolution has dramatically raised greenhouse gas concentrations. Growing numbers of people, farming, changing land usage, burning fossil fuels, making cement, and trash are some of the causes. The usage of fossil fuels and deforestation both contribute to climate change, with emissions reaching 2,100 parts per million [2].

The greenhouse effect and pollution are caused by CO_2 emissions and other gases. Within the last century, the average global temperature has risen by almost 2°F [3]. The use of renewable energy sources, such solar power, has become increasingly popular as a solution to these problems [4]. By lessening the burden on conventional electricity systems, battling climate change, and cutting greenhouse gas emissions, solar energy provides a sustainable solution [5]. In addition, trees are essential for improving urban air quality and reducing global warming [6]. Trees serve as organic carbon sinks by absorbing CO_2 and reducing the greenhouse effect [7]. Additionally, trees emit oxygen into the atmosphere, reviving it with pure oxygen and lowering air pollutants like PM, NO_x, and VOCs, all of which contribute to better air quality.

Finding appropriate sites for solar panel installations is one of the main obstacles to the expansion of the solar energy infrastructure. To optimize solar energy output while minimizing environmental impact, space must be used efficiently. Rooftops are an idle resource for solar energy development in metropolitan locations. Cities may lessen their dependency on fossil fuels, save electricity prices, and improve the environment by using solar energy from rooftops. The number of rooftop solar panel installations has increased in pace with the growing need for renewable energy production. Companies like Tesla [8] have commercialized solar roof tiles, which are now commonly placed in cities.

Keeping this in mind, our research focuses on detecting the rooftop areas from drone images and calculating the detected rooftop areas, considering available space for solar panel installation and tree plantation. Drones are used for cost-effective and efficient ways of capturing high-quality aerial images. By using image processing and computer vision techniques, we can successfully identify and delineate rooftop areas. We also provide insights on other environmental benefits from our research. We especially investigate the combination of solar panels and green infrastructure—that is, trees. In addition to their positive effects on air quality and carbon sequestration, trees also offer shade, which can increase the life and efficiency of solar panels.

Solar panels can significantly lower electricity use in many ways. One strategy is to move peak demand from on-peak to off-peak hours by integrating solar photovoltaic (PV) panels with Battery Energy Storage Systems (BESS) [9]. This lowers daily operation expenses. Installing solar panels on water surfaces is an additional tactic that can increase panel efficiency by 2.6% and prevent water from evaporating from dams, leading to increased electricity output and water conservation [10]. Furthermore, a microgrid system that is linked to the grid and has batteries and PV arrays can dramatically lower Indonesia's electrical energy usage by 56.7%, improving dependability and financial efficiency [11]. Moreover, approaches to lower energy usage in solar-powered wireless access networks during blackouts demonstrate encouraging outcomes, with possible energy savings of up to 72% in comparison to conventional grid reliance [12].

Planting trees is a feasible natural solution to lower air pollution and improve air quality in cities. Research indicates that street valley trees can act as biological filters to reduce PM (particulate matter) concentrations [13]. Nevertheless, trees' ability to control air quality depends on several factors, including their species, locations, and urban design [14]. Trees can help reduce air pollution, but before planting, consider carefully where and how many to plant to avoid blocking wind circulation as well as raising pollutant rates [15]. All things considered, carefully placing trees in metropolitan areas can help reduce air pollution and enhance air quality, resulting in healthier and more environmentally friendly cities to live in [16].

The results of the study will provide information about the feasibility and long-term viability of rooftop solar installations to stakeholders in renewable energy, policymakers, and urban planners. Our research aims to accelerate the shift towards a more resilient and sustainable urban environment by assessing the amount of rooftop space that is accessible, estimating the potential for solar energy generation, and suggesting additional green infrastructure. This may reduce the amount of global warming and tackle the issue over air quality. Using this, a total approximation can be done over an area about how much room in rooftops is available for setting up solar panels and planting trees in that area. This can lead to providing electricity from the national grid by calculating a building's production power.

Problem Statement

A lot of problems are getting worse in cities around the world, and they are putting both natural and social health at risk. As pollution levels rise, the quality of the air gets worse, and temperatures around the world keep going up, making the effects of climate change worse. Load shedding and power shortages have become routine at the same time, putting more stress on urban infrastructure and making daily life worse. A big problem with solving these problems is that there aren't any accurate ways to find and define empty places in cities that can be used for building things like green spaces or installing renewable energy systems. It is hard to find and make the best use of these available urban areas, which makes it harder to put in place long-term solutions that could help solve these important issues. We desperately need new ways to use urban areas to make the air better, lower temperatures, and increase energy security through renewable energy sources.

Research Gap

- Existing research primarily focuses on only detection of the rooftop areas, but they didn't provide any long-lasting solution to cope with the problems by combining renewable energy resources and green infrastructure.
- Many studies [23][26][28] rely on small datasets that are old, not proper and high-quality data. Many of the studies used google map and satellite data containing low quality and many studies [19] highlight the difficulties in using models to find rooftops on satellite images and suggest looking into other methods to get better classification results.
- For proper dataset preprocessing, proper augmentation and parameter tuning, total accuracy is a little bit low in some existing studies.

Existing studies aim to identify rooftops for development but lack long-term solutions for combining renewable energy sources with green infrastructure to address environmental issues in cities. Many studies use small, poor datasets, and insufficient satellite data for accurate planning and spotting. Issues with data preprocessing, addition, and parameter tuning further reduce accuracy. To address these gaps, advanced methods and large datasets are needed for improved detection accuracy and long-term solutions for urban growth.

Research Objective

As many of the studies used satellite images for the detection of rooftop areas, it is a little bit harder to detect accurately. Thats why the main objective of our study is to make a proper and high-quality dataset. Another objective is to detect the rooftop areas properly that will lead to successful installation of renewable energy resources. Better accuracy and structured deployment are also the objective of our study.

Motivation

The motivation is the serious problems that cities are facing, such as worsening air quality and higher energy costs. The rising cost of energy and the worsening air quality are big social problems that make life in cities less pleasant and contribute to climate change. Poor air quality is very bad for your health, and rising energy needs cause frequent power outages and "load shedding." This rising problem in society motivated me to work on this topic.

Our work adds to the fields of data science and deep learning by creating and using advanced algorithms for accurately finding rooftops from drone images. We want to raise the bar for the accuracy and efficiency of urban space utilization research by using large datasets and strong data preprocessing, augmentation, and parameter tuning methods. This study makes the field better by showing how deep learning models can be used to solve real-world environmental problems. This closes the gap between theoretical research and useful applications in real life.

Contribution

In this work I have tried to solve all the gaps. Such as using a clear and high-quality dataset using drone videography instead of using satellite data. Also, described a combined solution using outcome of the model like implementing renewable energy resources and green infrastructure in urban areas to reduce the temperature increase and air quality reducing problem. Proper dataset preprocessing and augmentation are used in it to get better accuracy. Using this technique, I was able to achieve better performance in detecting the rooftops and getting size of the detected free space to use in development tasks.

Summary

We talked about the world's most important environmental problems in part, including global warming, rising energy costs, and worsening air quality, all of which are made worse using nonrenewable energy sources. The goal of our study is to find rooftops in cities that are good for putting green infrastructure and renewable energy sources so that these problems can be solved. With the help of deep learning and drone images, we hope to correctly locate rooftop areas that can be used for projects like installing solar panels and planting trees. The goal of this study is to show that mixing solar energy with green infrastructure could help lessen the effects of climate change and make cities more environmentally friendly. In the next section, we'll take a close look at the existing research, which will shed light on the methods, limits, and recent progress in the areas of rooftop detection and sustainable urban development.

Chapter 2

Literature Review

Introduction

As a researcher, I evaluated earlier work, and research in the literature review segmentation. By this I have learned what research has previously been performed and a general overview of this domain. I have focused on what methods previously used in this kind of study, datasets, and findings. Finally, after analysis, I focused on the limitations of previous studies and based on these limitations my goal is to improve results.

Previous Literature

In recent years, the cities have been looking for long-term solutions to problems with energy use and urban growth by using rooftops to create green spaces and generate renewable energy. Effective planning and execution of solar panel setups and tree planting projects require accurate size calculations and finding rooftops. Finding gaps, challenges, and possible paths for more study and practical applications in this field depends on knowing what has already been written in the area. The point of this literature review is to look at the most recent studies on finding rooftops and figuring out their sizes, especially when doing things like planting trees and solar panels. This review combines the current knowledge and methods to show the progress, limitations, and possible future directions in this important area of urban sustainability.

In this paper [17], rooftops are detected using aerial RGBD and near infrared data, enabling calculation of actual free roof area for applications like solar panel deployment with an F1 score of 88.27%. It discusses the benefits of urban trees in reducing air pollution and the heat island effect, but neglects challenges in implementing these strategies, the effectiveness of different tree species, and the long-term sustainability of large-scale tree planting.

Not the exact work but a similar work is done in this paper [18]. It uses Convolutional Neural Networks on aerial images to automatically find and size rooftop solar panels. It works 94% of the time and has an Intersection over Union score of up to 0.64. The research paper employs Convolutional Neural Networks (CNNs) as the primary model for detecting rooftop solar panels from high-resolution aerial photos. The performance of the model could still be better. Also, the article makes it sound like the current framework can only find certain forms and that it needs to be expanded in the future so it can be used for more things. To help more people use solar technology, we also need to make it easier to see how socioeconomic factors affect the spread of photovoltaic (PV) systems.

Related work [19] is done about an automated method for modeling 3D building roofs. It has two main parts: roof detection and 3D geometric modeling. A 94% success rate for automated rooftop detection and a 12% omission mistake. Roof size was figured out using geometric modeling techniques that gave a 96% median accuracy and 88% completeness. The accuracy of the method rests a lot on the quality and resolution of the datasets that are used as input, and it has trouble with roofs that are close to areas with lots of trees or plants. 3D edge extraction from pictures of small buildings is hard, and wall modeling is often wrong, especially without LiDAR data. The method works best when either picture matching is used with LiDAR DTM data or LiDAR data is used for Digital Surface Models (DSM), Digital Terrain Models (DTM), and normalized Digital Surface Models (nDSM).

This study [20] proposes an automated method for roof area calculation, aiming to improve efficiency and reduce errors in architectural projects. It includes figure recognition, dimension calculation, connection identification, 3D visualization, and calculation based on processed data. The goal is to reduce manual effort, increase accuracy, and ensure consistency. It works well with a mean relative error of 1.02%, which is fine for roofing companies, and can handle partial roof surface information. Users can also provide architectural plans. However, it's not fully automated because the user must add information for the roof model, and it doesn't have a way to figure out the area of non-flat roof surfaces, which shows that it needs to be improved in the future.

Baluyan et al. [21] used support vector machine (SVM) classification on Google Maps photos to find rooftops in their study. However, the authors said that this method did not work well. To get around this problem, they suggested finding more useful features for the classification process and using different models, like the unbalanced SVM. This study highlights the difficulties in using SVM to find rooftops on satellite images and suggests looking into other methods to get better classification results.

Sentinel-2 satellite images were used in Kumar's work [22], which used Canny contouring and thresholding techniques. The sizes of these pictures are set. Using a branched network for feature embedding and multiclass classification is what the paper suggests. The paper suggests a new way to figure out how much solar power a building's roof could produce just by looking at where it is. To be sure it works, they put it to the test on different kinds of roofs. This method tells you about the best places to put solar panels on your roof and gives you an idea of how much space you can use for them. They had special ways of finding roofs and drawing out the best spots, even in pictures that weren't very clear. The study also says that to improve the process even more in the future, more advanced methods should be used.

Convolutional neural network (CNN)-based automatic rooftop recognition method for building extraction in Christchurch is described in this article [23]. Aerial dataset that covers 450 km^2 after the earthquake is preprocessed by splitting the picture into patches. Skyscraper detection uses Mask R-CNN, a system for finding and separating objects. The Framework uses RPN and RoIAlign for feature matching, and ResNet 101 for feature extraction. To ensure accurate identification, the dataset has more than 220,000 buildings split into training and testing sets. Using Mask R-CNN, the process includes steps for feature extraction, region proposal network (RPN), binary mask generation, and object classification.

The main topic of the study [24] is finding the edges of roofs to make installing solar panels easier. It talks about how important edge recognition is for getting useful information from pictures. This method uses satellite pictures, even ones with things in the way like trees, to get rid of those things, fix the images, and find the exact edges of roofs so that solar panel planning works well. In their study they lack the automation process.

Another study [25] describes a rooftop planting system that aims to make an eco-friendly and long-lasting answer for urban rooftops by controlling the outside temperature, stopping heat loss, and encouraging the flow of fresh air. For this method, insulating materials and squared timbers are fixed to the roof to make a base for the plants. After the squared logs are put together, louvers are put on top to create air layers that keep heat in. Finally, waterproof sheets are added to protect against water damage. Sedum blocks are stuck on top of these sheets to make them even better at keeping heat and cold out. Ventilating ports are put in so that air can flow properly, and rainwater can drain through draining passageways. The sedums that grow inside the blocks aid in the cooling effect and energy efficiency of the system. Overall, the system uses shielding, air flow, and plants to make a green, sustainable rooftop environment that saves energy and lessens the effects of heat islands in cities. The current planting system talked about in the study paper is only useful for planting trees on roofs. It doesn't work well in other places where trees could be planted in an eco-friendly way. The climate and environmental conditions of the rooftop site may affect how well the system works, which in turn could affect how well the plants grow and stay healthy.

A study [26] has successfully extracted building roof points from 3D point cloud data using optical aerial images. The algorithm, which calculates normalized difference vegetation index (NDVI) values and identifies vegetation cover points, achieved high accuracy levels comparable to or better than studies using LiDAR data. Future work aims to enhance accuracy by eliminating false roof planes and refining geometric shapes to reflect actual roof planes more accurately. This highlights the potential of dense image matching technique in automatic building roof detection, showcasing its effectiveness in generating high-accuracy 3D models for remote sensing and urban planning applications. As part of the study, the model's ability to automatically pull-out building roof points from thick networks of matching points was tested. Most of the tests were right 95% of the time, all of them 98% of the time, and good 93% of the time. There was a high level of accuracy in the suggested algorithm for automatic roof point detection, as shown by scores of 93.8% to 98.3% correctness, 97.3% to 98.7% completeness, and 91.5% to 97.0% quality. There are some good things about using high-resolution pictures to make 3D point clouds for extracting roof planes, but there are also some limitations. Some types of vegetation, shadows, and missing or wrong data can make it hard to get rid of most vegetation and ground points. This is especially true in shaded places where roof planes might not be visible. Even though they did well on tests, they can still do better, especially when it comes to filling in gaps caused by shadows. In the future, work will be done to automate roof point extraction to improve accuracy and make high-precision orthogonal images with this method.

The article [27] talks about how machine learning can be used to make it easier to find rooftops in aerial photos, which is an important step in recognizing pictures taken from above. Through ROC analysis, four methods were looked at with a focus on skewed data sets and different error costs. Three tests were done to investigate different parts of using machine learning to analyze images. These tests showed how well naive Bayes and a custom classifier worked. The study shows how important it is to use experimental methods to compare different approaches when the classes aren't balanced, and the mistake costs are different. Using picture data, the experiment tested how accurate different models were. At 0.963, the C5.0 method was the most accurate. At 0.961, the k-NN method came in second. Other models, such as k-NN (k 11), k-NN (k 5), and Perceptron, also did very well. With a false positive rate of only 0.02, the Perceptron model did a good job of reducing false positives. In this case, the results show how well different models do at finding rooftops.

In another study [28], a machine learning-based rooftop detection method was proposed for solar PV installation planning in urban areas. A pilot study in Abu Dhabi, UAE, demonstrated its utility in two residential areas. The study compared three PV technologies, finding thin-film panels may offer advantages despite high initial costs. The environmental benefits of PV technology could outweigh the costs, especially with subsidies and feed-in tariffs. Unfortunately, there are some problems with the study that look at rooftop solar PV potential and economic viability. It is limited to Abu Dhabi, UAE, uses old Google Maps data, and believes that energy production, costs, and incentives will change over time. Beyond internal factors, such as government policies, market conditions, or technical progress, the analysis does not look at these things. Either the environmental effects or the social and economic effects that go beyond financial gains are not measured.

The paper [29] describes a new way to figure out how much rooftop PV solar energy can be used across the whole country, with a focus on Switzerland. It combines Geographic Information Systems (GIS), solar models, and machine learning (ML) methods, more specifically random forests. The study's goal is to give correct estimates of the PV potential of each (200x200) pixel grid that covers the whole country. These estimates will consider factors such as roof area, shape, slope, solar radiation, and shading. The method uses a hierarchical structure and includes data from many sources, such as LiDAR data for estimating shade and satellite data for figuring out radiation. The results show that rooftop

PV installations in Switzerland have a lot of promise. They could produce as much as 16.29 TWh of electricity per year, which is about 25.3% of all the electricity that was needed in 2017. Using prediction intervals to show how accurate the models are, Random Forests outperforms other machine learning methods in terms of both accuracy and how quickly it can do its job. Researchers, energy service companies, stakeholders, and cities can use the study's findings to better understand and use rooftop PV power on a regional or national scale.

Another study [30] investigates how rooftop PV systems could grow in Hong Kong and how they can help the environment. It thinks the maximum power that could be installed is 5.97 GWp, which would produce 5981 GWh of energy each year and add 14.2% to all the electricity that was used in 2011. The study also found that by changing the local energy mix, about 3,732,000 tons of greenhouse gas (GHG) emissions could be avoided each year. There are different kinds of rooftop PV systems in Hong Kong. The energy payback time (EPBT) and greenhouse gas emission payback time (GPBT) run from 1.9 to 3.0 years and 1.4 to 2.1 years, respectively. These are both much shorter than the 30 years that the systems are supposed to last. The energy yield ratio (EYR) is between 10 and 15, which means PV Systems on roofs could produce at least 10 times the energy they need over their lifetime. Even though it costs a lot to install PV electricity in Hong Kong right now, it should soon be able to compete fully with other types of electricity with the right subsidies, carbon credits, and lower installation costs. The paper says that the government should make energy policies that are more proactive and set aggressive goals for the growth of PV technology. The main goal of the study was to look at the technical, economic, energy, and environmental potential of rooftop PV systems in Hong Kong. It gives answers to questions about PV power, making electricity, and possible environmental benefits. Researchers didn't say how accurate the models they used were, but they did a lot of research into things like solar radiation, building characteristics, installation prices, and environmental effects to come up with their method and results.

Summary

From the above studies, I can conclude that many processes and ways are used for rooftop detection and setting up solar panels and green trees. However, very few studies mentioned various approaches and various model accuracy and their various datasets. Maximum work has been done in deep learning. In my research work, I tried to solve their shortcomings as much as I could.

Chapter 3

Methodology

3.1 Introduction

In this thesis, "Rooftop Detection, Size Estimation, and Eco-friendly Infrastructure Planning," the predictive power of the YOLOV5 and YOLOV8 models is accessed in an organized fashion. First comes data gathering, next comes data preprocessing and feature engineering. These are the main steps of the process. Using well-established measures, each model's performance is thoroughly assessed, allowing for a comparison study to y to identify each one's advantages and disadvantages uniquely. The approach considers interpretability, practical insights, and temporal considerations as essential components, offering a thorough basis for precise and effective detection and estimation of roofs.

3.2 Methodology (Possible Method-Diagram)

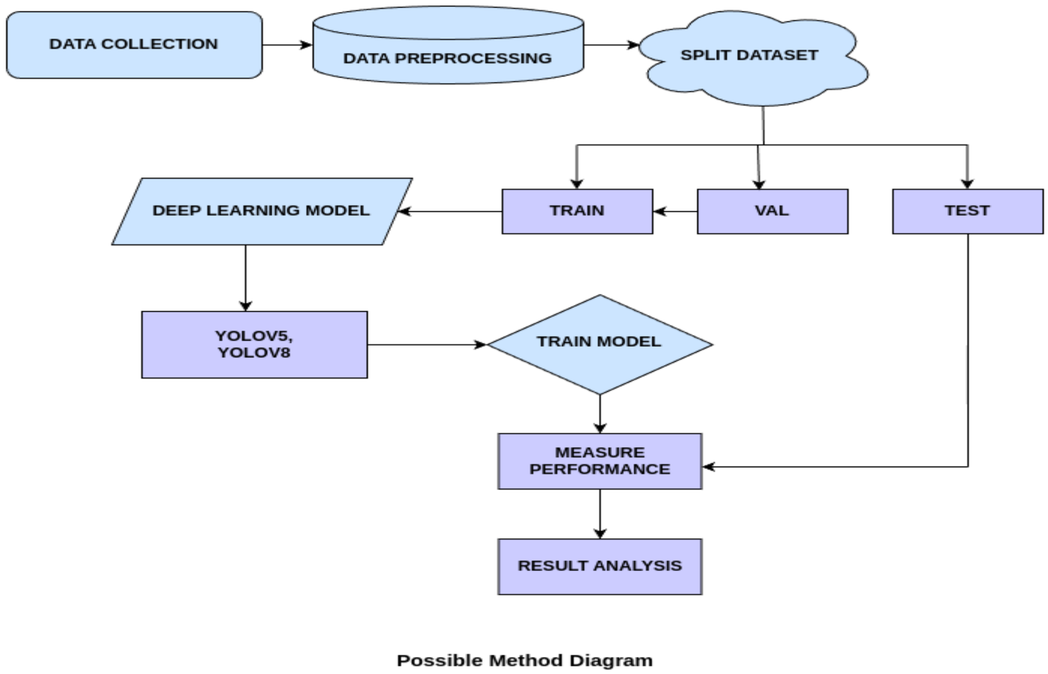

Figure 1-Possible Method Diagram

3.3

3.3.1 Data Collection

We have collected the data by collecting videos from some areas of Dhaka. That is some drone footage collected in various times. Then converted the videos into images.

Figure 2-Image of the Dataset

3.3.2 Data Preprocessing and Augmentation

From the footage, we have extracted frames for our training purposes. This gave us about 935 images from the video footage. These photos were then annotated in YOLO format with the Roboflow tool. After augmentation, the images turned into 2335 photos resulting in 2335 text annotation files. One class of annotations was identified. We used augmentation and preprocessing to address any overfitting concerns.

Preprocessing	Auto-Orient: Applied
	Resize: Fit within 640x640

Figure 3-Preprocessing

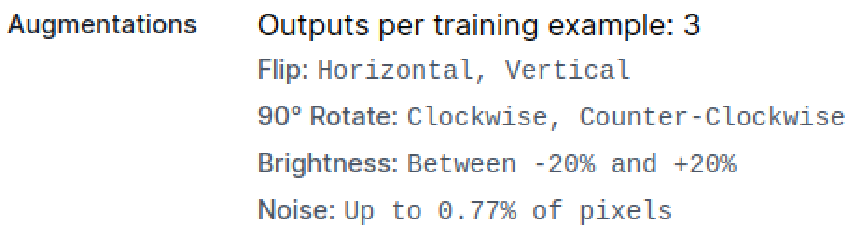

Figure 4-Augmentation

3.3.3 Dataset Splitting

The gathered dataset was divided into training, validation, and testing subgroups during the data splitting stage. For an appropriate evaluation of the prediction models, the divide is important. Split ratios are often used such as 80-20 or 70-30. But here we used 90% for the training dataset, 4% for validation and 6% for the testing dataset. Training subgroup received most of the data. In the meantime, the testing subgroup provided unseen data to evaluate the generalization performance of the models, ensuring that the deep learning models gain knowledge from a significant amount of the data.

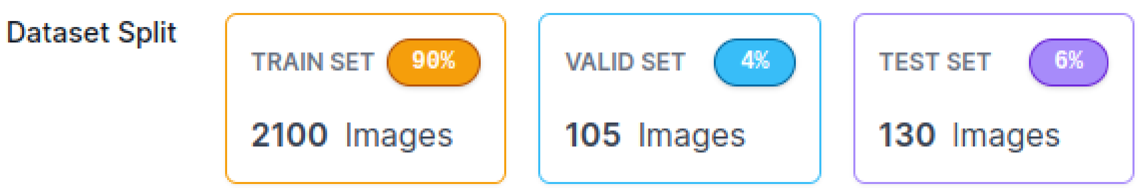

Figure 5-Dataset Split

3.3.4 Model Selection

For our object detection assignment, picking the right models was a very important part of our research process. As part of our review process, we set standards for things like accuracy, speed, model size, community support, and how well the model works with our dataset and framework. The versions that were looked at were YOLOv3, YOLOv4, EfficientDet, and SSD. However, YOLOv8 and YOLOv5 were found to be the best options. A better version of YOLOv4, YOLOv8 stood out for its cutting-edge performance and ability to work with well-known deep learning systems. Its high accuracy and improvements in speed and efficiency made it a good choice for our study. But YOLOv5, which is known for being easy to use and able to make inferences in real time, was much more accurate and had a large community behind it. Our comparison, which included testing the models on our dataset, showed that both YOLOv8 and YOLOv5 had good points. They were the best choices for our thesis because they were accurate, fast, and compatible. They gave us a solid base for our object recognition experiments and analysis.

3.3.5 Model Training

The training step included providing the training data to the chosen deep learning models (YOLOV5, YOLOV8) so they could pick up on patterns and connections found in the dataset. To optimize each model's performance, hyperparameters were adjusted during the process. By taking this vital step, it was made sure that the algorithms were properly trained to generate accurate predictions on fresh and untested data.

3.3.6 Model Testing

Utilizing a different testing dataset, the performance of the trained deep learning models (YOLOV5, YOLOV8) was evaluated during the testing stage. The purpose of the assessment was to see how effectively each model might generalize to fresh, untested data. A quantitative assessment of each model's accuracy was obtained by contrasting its projected prices with the actual prices found in the testing dataset. Understanding how well the models function in actual situations and their capacity to provide accurate prediction on data that hasn't been seen before depending heavily on this stage.

3.3.7 Performance Measurement

To evaluate how well YOLOv5 and YOLOv8 worked on our dataset, we used both quantitative and qualitative methods. The quantitative measures we used were mean average precision (mAP), precision, recall, and inference time. To figure out how accurate object recognition was, we used mAP, which takes into account how well both models could find objects across a range of classes and confidence levels. To see how well the models did at reducing false positives and false negatives, precision and memory were tested. In addition, we looked at the inference time to see if they could be used in real time. We looked closely at the model's predictions on sample images to see how well they worked in real life. By comparing how well the models did on these metrics, we were able to choose the best model for our object detection job.

3.3.8 Size calculation

We are using shoelace formula to calculate the size of the segmented rooftop areas. The formula works for any simple polygon. Suppose given the vertices of the polygon *(x1, y1), (x2, y2) ....(xn,yn)*, the area is calculated as:

$$A = \frac{1}{2}\left|\sum_{i=1}^{n}(x_i\, y_{i+1} \; - \; y_i\, x_{i+1})\right|$$

where (xn+1, yn+1) is assumed to be (x1, y1) to close the polygon.

To find the area of the segmented roofs in the picture given, the steps below are used. So that it can be processed more easily later, the picture is first loaded using OpenCV and turned into a grayscale file. As a result, a binary mask is made by setting all non-zero values (which are the blue masks) to 255 (white) and all other values to 0 (black). This separates the divided areas perfectly. Utilizing cv2.findContours, the edges of these divided areas are identified, which serve as the roofs' edges. This makes the shape easier to understand by comparing each curve to a polygon with cv2.approxPolyDP. This is followed by using the Shoelace method on each polygon to find its area. Lastly, the boundaries of all the segments are printed, and Matplotlib is used to show the picture with the lines drawn on it. This lets you see that the areas that were calculated and segmented are correct. We can accurately find the rooftop areas from the divided masks using this method.

3.4 Individual Model

3.4.1 YOLOv5

YOLOv5, which was made by Glenn et al. soon after YOLOv4 came out, is a big step forward for the YOLO series. Nepal and Eslamiat [31] say is that YOLOv5 is different from the earlier versions because it uses PyTorch instead of Darknet. This makes it more flexible and compatible with other PyTorch-based models. This change to the architecture makes it easy to try new things and connect to the PyTorch ecosystem. YOLOv5 is based on CSPDarknet53, which was chosen because it was good at fixing the problem of repeated gradient information that was present in earlier versions of YOLO, especially in YOLOv4 and YOLOv3. The YOLOv5 algorithm uses CSPDarknet53 to lower network parameters while keeping or even better accuracy. This makes the computation more efficient.

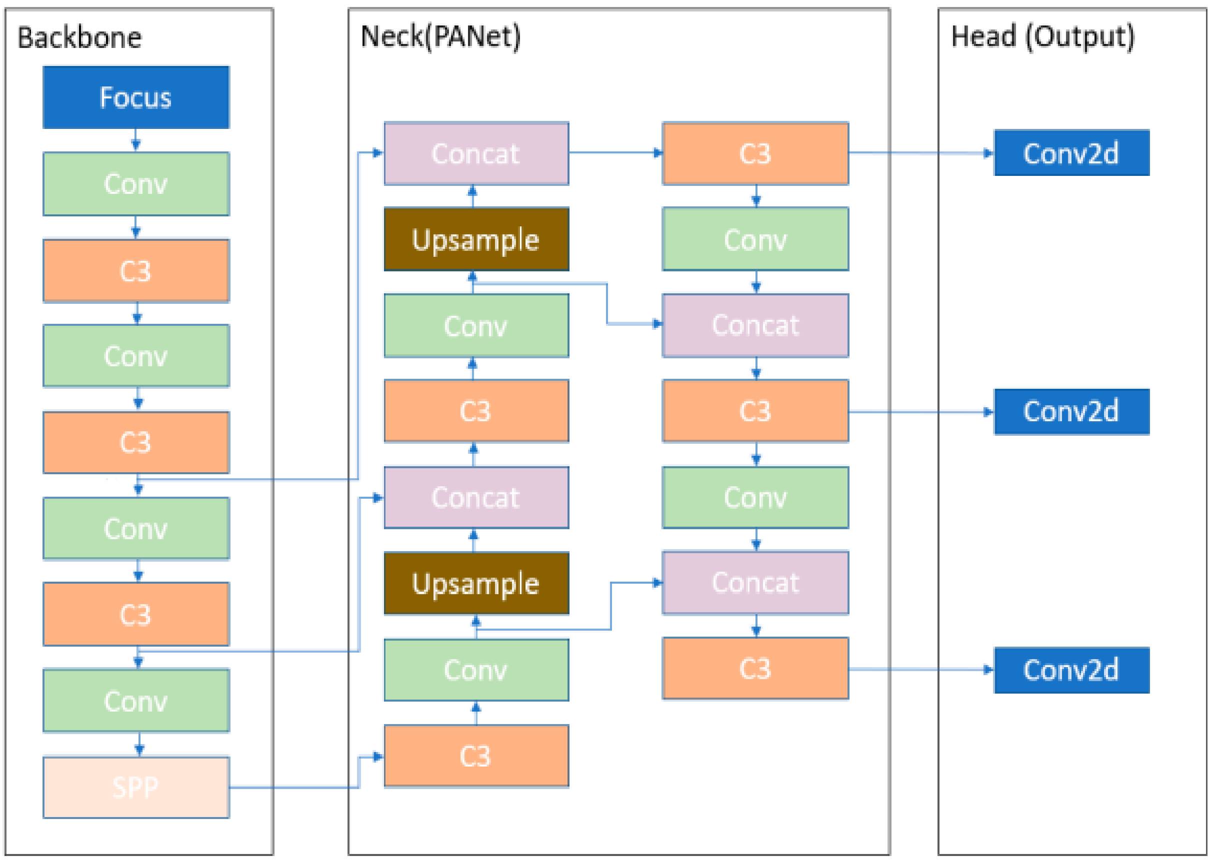

Figure 6- YOLOV5 Architecture (Nepal and Eslamiat, 2022)

YOLOv5 has a lot of important architectural changes that make object recognition work better. It is important to note that the Path Aggregation Network (PANet) was added as the model's neck. A Feature Pyramid Network (FPN) with both bottom-up and top-down paths speeds up the flow of information within the network. This design makes it easier for low-level features to spread throughout the model. This improves the accuracy of localization and makes it easier to find objects exactly at different sizes and in different settings. PANet also includes a Spatial Pyramid Pooling (SPP) block, which makes it easier for the model to deal with items of different sizes and aspect ratios. Also, YOLOv5's head design keeps parts of its predecessors, YOLOv4 and YOLOv3, making three separate feature maps for multiscale forecasting. This makes sure that the model can catch things well at different sizes and resolutions. Using the GIoU-loss method, which is like what YOLOv3 does, also makes object localization even more accurate.

In conclusion, YOLOv5 is a strong and effective object recognition model because it focuses on organization, uses CSPDarknet53, PANet with FPN and SPP blocks, and the GIoU-loss function. The latest version of YOLO is better than earlier ones because it fixes bugs and adds new design features that make it more accurate, faster, and able to handle more users [32].

3.4.2 YOLOv8

The newest member of the YOLO family is Yolov8. Redmon et al. [33] came up with the first YOLO model. People have always known that the YOLO model series is the best at finding objects. After a few changes, Jocher et al. [34] came up with the YOLOv8 model. YOLOv8 builds on the success of the previous YOLO series by making several important changes. An anchor-free sensing head has been added, which is a big change. Instead of using anchor boxes like earlier versions did, YOLOv8 directly guesses where the object's center is. This means that there is no need for IOU matching or assigning scales on one side, and it uses a task-aligned way to match positive and negative samples. This makes the model easier to understand and better able to handle things that are small or overlap. Besides that, YOLOv8 swaps out the C3 module from YOLOv5 for a new C2f module. The C3 module is CSPDarknet53 with 3 convolutions. Based on the original C3 module, the C2f module cuts the network down by one convolutional layer. This program makes computations faster without slowing them down. The way it does this is by mixing the best parts of previous YOLO models. The C2f module allows for a more complete flow of gradient data while keeping the structure light.

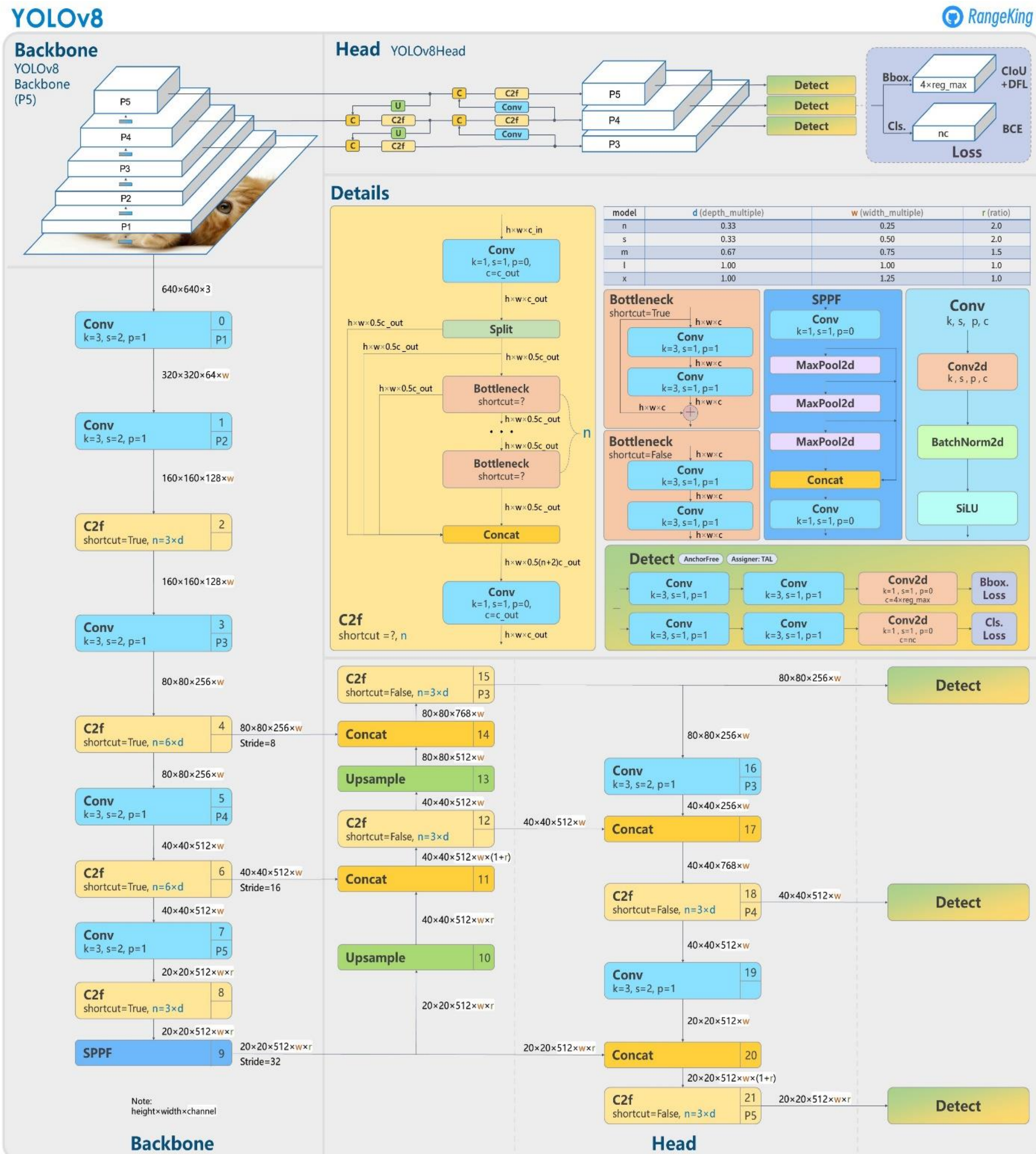

Figure 7- Model structure of YOLOv8 detection models.[35]

The general structure of YOLOv8 is shown in Figure 2. YOLOv8 takes ideas from the Path Aggregation Network (PAN) [36] and combines features from different feature maps of different resolutions to make multi-scale features. The input picture is sampled five times by the backbone. This makes five scale feature maps, which are labeled as {P1, P2, P3, P4, P5}. The main job of the backbone is to pull out these useful features from the input picture. The neck comes after the backbone and connects the extracted features to the sensing head. The neck improves these traits and makes it easier for them to work together, so the detection head can use the most useful representation to find objects. Finally, the recognition head will find objects. It's important to note that in YOLOv8, the scale set {P3, P4, P5} is very important. Each scale oversees finding items in a certain size range: P3 is for small objects, P4 is for medium objects, and P5 is for large objects. This splitting of work between sizes makes the model better at finding things overall.

3.5 Evaluation methods

To analyze the data, I have constructed a confusion matrix, a useful tool for evaluating the performance of a detection model. The confusion matrix includes matrices such as true positive (TP), true negative (TN), false positive (FP), and false negative (FN).

In the context:

- A true positive (TP) represents instances where the model correctly predicts a positive outcome.
- A true negative (TN) is when the model accurately predicts a negative outcome.
- A false positive (FP) occurs when the model incorrectly predicts a positive outcome.
- A false negative (FN) is when the model incorrectly predicts a negative outcome.

3.5.1 Accuracy

The accuracy of a machine's predictions is directly linked to the quality of the model. When all classes are given equal weight, overall accuracy becomes a significant metric. In the context of my work, where each class holds equal importance, it is crucial to consider accuracy as a key measure in evaluating the model's performance. Accuracy provides a comprehensive view of how well the model predicts across all classes, serving as a fundamental indicator of its effectiveness in making correct predictions.

Accuracy = $\frac{(TP + TN)}{(TP + FP + TN + FN)}$

3.5.2 Precision

In machine learning, precision is a metric that gauges a model's effectiveness in performing its task. The calculation for precision involves dividing the number of true positive predictions by the total number of positive predictions, providing a measure of how accurately the model identifies instances it predicts as positive. Precision is particularly valuable when there is a need to minimize false positives and ensure that positive predictions made by the model are reliable and accurate.

Precision = $\frac{True\ positive}{True\ positive + False\ positive}$

$$\frac{True\ positive}{Total\ predicted\ positive}$$

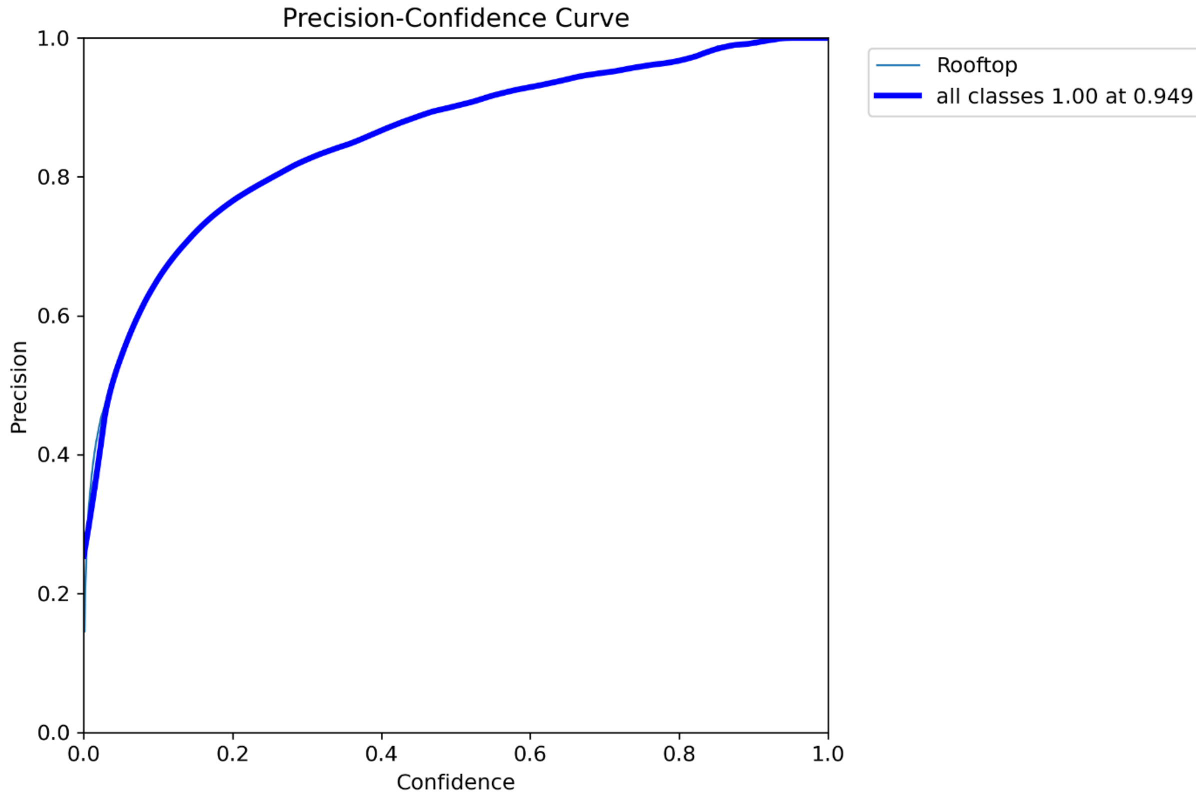

Figure 8-Precision

3.5.3 Recall

The term recall in the context of machine learning involves calculating the number of correctly detected true positives. To compute recall, we divide the number of true positive predictions by the total number of accrual positive instances, providing a measure of the model's ability to identify all relevant instances within a given category. Recall is particularly important when the emphasis is on minimizing false negatives and ensuring that the model captures a high proportion of actual positive instances.

$$\text{Recall} = \frac{True\ positive}{True\ positive + False\ negative}$$

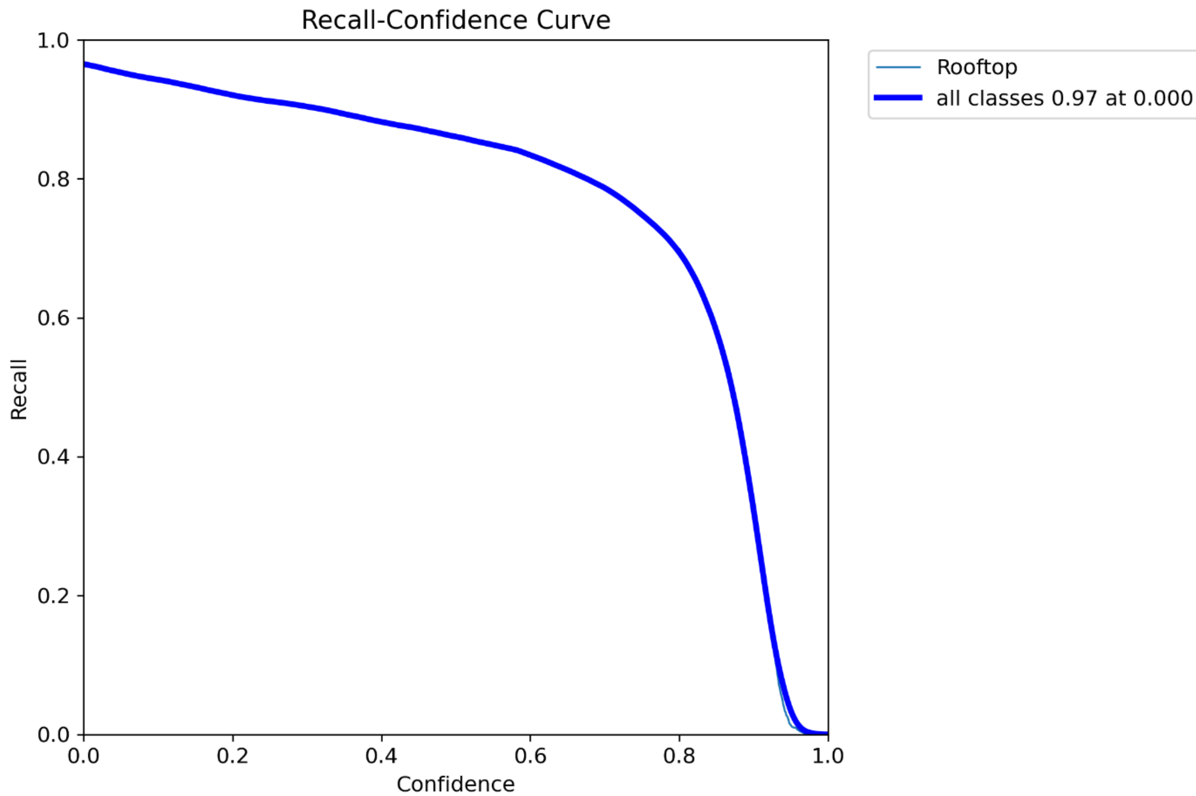

Figure 9-Recall

3.5.3 F1 Score

To check classification models, the F1 score looks at both accuracy and recall, which is especially important for datasets that aren't fair. It gets the right mix of real positives and projected positives that are true. False positives and negatives are important in many areas, such as medical diagnosis and fraud detection. This is very important.

$$F1 = 2 * \frac{\Pr ecision \cdot Recall}{precision + Recall}$$

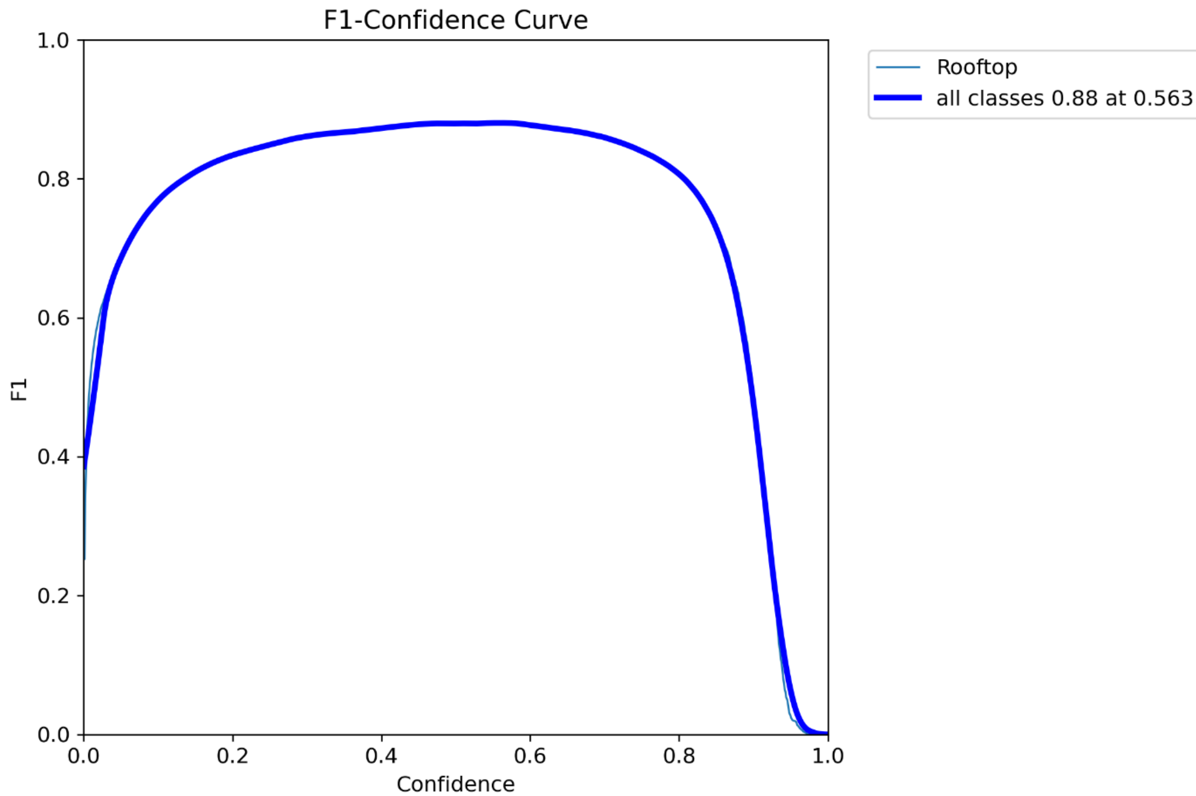

Figure 10-F1 Score

3.6 Summary

In this part I have described the whole working process to find the detected areas and the model structure using basic diagrams. Dataset cleaning, preprocessing, augmentation, model training and the result parameters have already been described in this part. In the next part the result and performance comparison between models are described and various metrices and diagrams have been used to demonstrate the result.

Chapter 4

Result and Discussion

Introduction

The result section provides a thorough summary of the findings and insights obtained from the study, serving as a testament to the condition of intensive research and analysis. This part presents and explains the results of the experiments, analysis, and models used to get knowledge of the information discovered throughout the investigation.

Result & Discussion

At the time of training the model learnt about many features and the images below represent the image learning process.

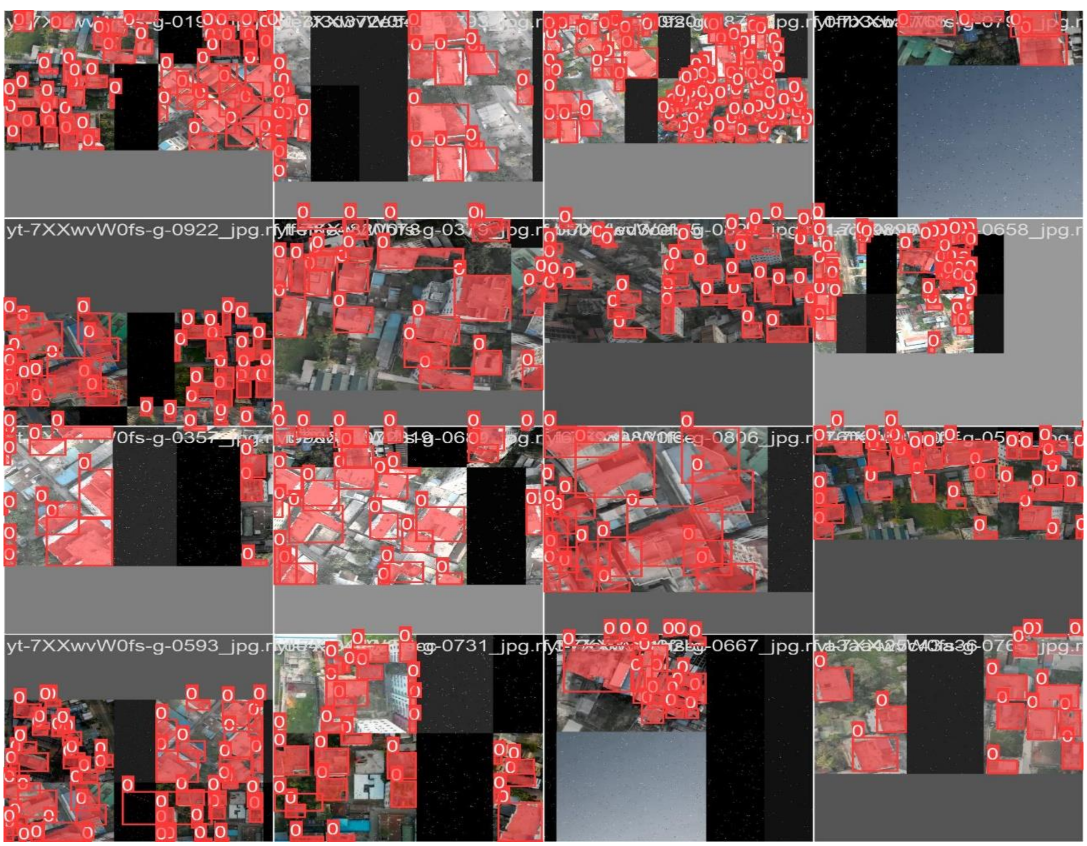

Figure 11-: Training Batch

Figure 12- Validation Batch (Labels only)

Figure 13- Validation Batch (Labels and Prediction)

4.1 Models Performance

After completing 25 training epochs, our YOLOV8 model achieved

Label	Value
Precision	~0.90
Recall	~0.85
mAP50	~0.90
mAP50-95	~0.75

In conclusion, the model does very well in the "rooftop" class, with high scores for precision and recall. A value of about 0.90 for mAP50 means that the model has a high mean average accuracy at the 50% IoU threshold. A value of about 0.75 for mAP50-95 shows the mean performance across a range of IoU thresholds. Based on these measures, it looks like the model is good at finding rooftops.

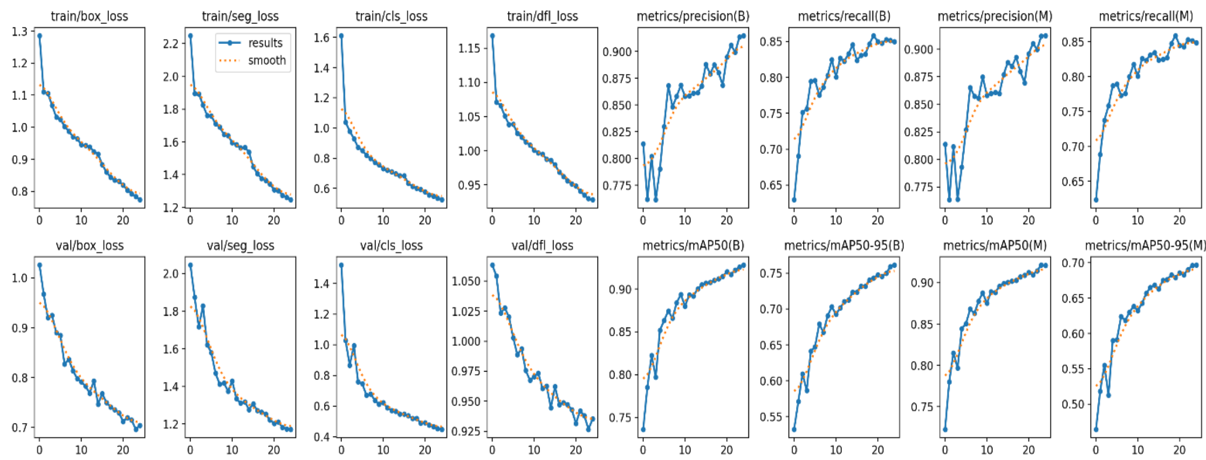

Figure 14- Total Result (YOLOV8)

After completing 25 training epochs, our YOLOV5 model achieved

Label	**Value**
Precision	~0.91
Recall	~0.87
mAP50	~0.93
mAP50-95	~0.72

In conclusion, the model does very well in the "rooftop" class, with high scores for precision and recall. A value of about 0.93 for mAP50 means that the model has a high mean average accuracy at the 50% IoU threshold. A value of about 0.72 for mAP50-95 shows the mean performance across a range of IoU thresholds. Based on these measures, it looks like the model is good at finding rooftops.

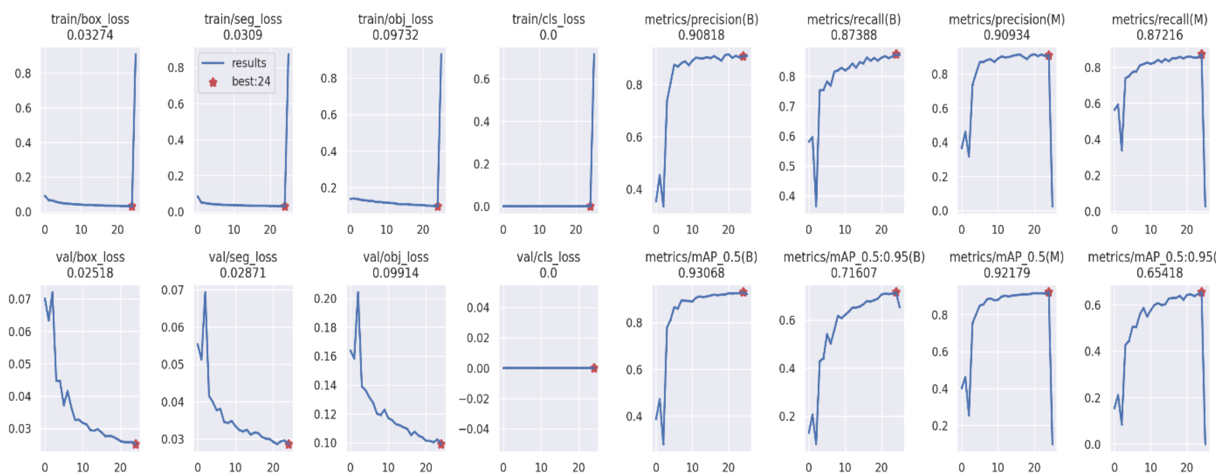

Figure 15- Total Result (YOLOV5)

4.2 Comparison between these two models

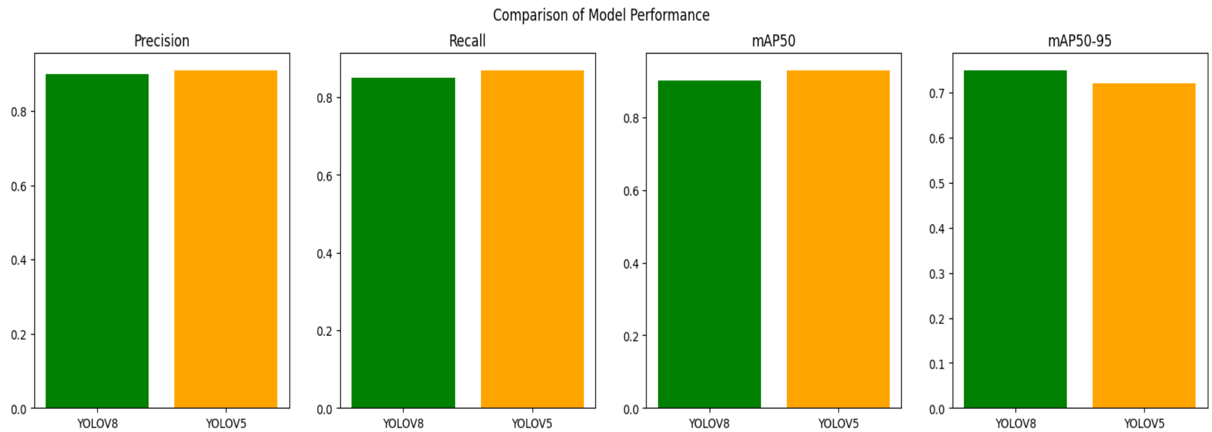

Figure 16- Comparison of model performance

Here,

- Model 2 is a little more accurate and has a better memory than Model 1.
- In terms of mAP50, Model 2 also does better than Model 1.
- The mAP50-95 of Model 1 is better than that of Model 2.

According to these tests, both models do a good job, but Model 2 does a little better in precision, memory, and mAP50, while Model 1 does a little better in mAP50-95. It's possible that this means Model 1 is more stable across a range of IoU thresholds, while Model 2 is better at the exact 50% IoU threshold.

4.3 YOLOV8 Output

After running the model using YOLOV8, the testing dataset is run into this trained model and the output is returned by the best fitted model. On the outputs, the model returned detected images. Here some of the detected output is given below:

Figure 17- YOLOV8 Output

4.4 YOLOV5 Output

After running the model using YOLOV5, the testing dataset is run into this trained model and the output is returned by the best fitted model. On the outputs, the model returned detected images. Here some of the detected output is given below:

Figure 18- YOLOV5 Output

4.5 Deployment

With the help of a Streamlit I created that is hosted on Hugging Face, users can determine how much rooftop space is available for installing solar panels or trees by entering the distance from which a rooftop photo was taken, the size of the solar panels or trees they want to install, and the rooftop image they want to upload. The application measures the image according to the specified distance, applies a scaling function to the image, and determines the usable area. After that, it makes an educated guess as to how many solar panels or trees can fit and shows where they would look visually. This application helps homeowners, environmentalists, and urban planners make the most of rooftop areas for sustainable projects.

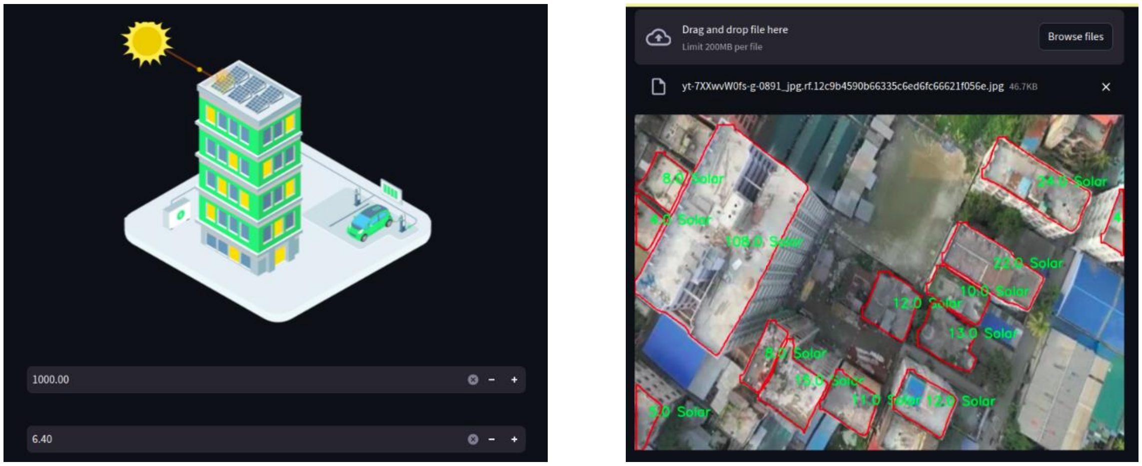

Figure 19- Deployment

4.6 Summary

Model 2 does better than Model 1 in terms of precision, memory, and mAP50, which means it is more accurate and consistent at the 50% IoU level. Model 1 does better on the mAP50-95 metric, which suggests it is more stable across a wider range of IoU levels. Overall, Model 2 is a little better because it has higher precision, recall, and mAP50 values. However, Model 1 may be better for some applications because it is more consistent across different IoU levels. So, Model 2 is the best choice if you care most about accuracy, recall, and mean average accuracy at the 50% IoU threshold. Model 1 is the best choice if you care more about consistency across a range of IoU levels.

Chapter 5

Implementation and Conclusion

Implementation

Solar Panel Installation: This rooftop data can be implemented in installing the solar panel on the rooftop. Many improving countries are now adapting this system for maximizing energy production to help in the main grid of country. The data tailors solar panel installations based on the precise rooftop dimensions and orientations. For this the users can reduce their energy consumption and they can produce their own energy.

Optimized Energy Distribution: From this, the authority can tie billboards in front of the buildings that provide the information about this building's roof, that means how much KW solar power based this rooftop is. The main agenda is generating your own electricity and reducing dependence on grid power, leading to significant savings on electricity bills.

Figure 20-Knowledge Tower 350KWP Rooftop Solar System

Distribution from national grids may be like this, the buildings will get power from national grid only which amount they needed considering their production capability from the rooftop. If every building can implement this, huge amounts of electricity can be exported after reaching the consumption of countries people.

Implementing micro-grid or Community Solar Project: The information from rooftop detection can also help make microgrids or community solar projects possible. Micro-grids are small, limited grids that can disconnect from the main grid and run on their own. Rooftop solar data can be used by micro-grids to make sure that energy is distributed and managed efficiently in a community. Community solar projects can share a solar power system so that many people can gain from it. This way, people who don't have good rooftops for solar installations can still get clean energy.

Utilizing Data by policy makers and cite planners: Rooftop data can help policymakers and city planners make better decisions and come up with better plans for urban growth. Having accurate data on rooftops helps people make smart choices about zoning, building codes, and incentive programs that encourage people to use solar electricity and other green technologies.

Green Rooftop Implementation: Roofs can be turned into green roofs instead of solar panels, which can greatly reduce urban heat islands, increase biodiversity, and make the air better. Rooftop data helps find good places to put green roofs so that they have the most environmental benefits.

Urban Agriculture: Rooftops can also be used for urban farming, which helps grow food locally and is good for the environment. Rooftop data helps figure out which roofs are best for urban farming by looking at things like how much sunlight they get, how much weight they can hold, and how easy they are to get to.

The results show that there are complex trade-offs between being accurate and being consistent. They can help people who work with green energy, urban planning, and protecting the environment. This study helps us learn more about how deep learning can be used to solve important sustainability problems by showing us the pros and cons of YOLOV5 and YOLOV8 in the areas of rooftop recognition and planning eco-friendly infrastructure.

Conclusion

The main goal of the study is to find rooftop places, guess how big they are, and plan an infrastructure that is good for the environment. This thesis, "Rooftop Detection, Size Estimation, and Eco-Friendly Infrastructure Planning Using Deep Learning," ends with a detailed look at two deep learning methods, YOLOV5 and YOLOV8, which are accurate 93% of the time and 90% of the time, respectively. The study carefully moves forward by collecting, cleaning, and preprocessing a lot of data before each model is trained and tested. During the assessment stage, the models are put through a lot of tests, and their success is judged by important metrics. The results show that both YOLOV5 and YOLOV8 are good at finding rooftops and estimating their sizes. However, YOLOV8 has slightly better accuracy, recall, and mean average precision (mAP) at the 50% Intersection over Union

(IoU) level. However, YOLOV5 is more stable across a wider range of IoU thresholds, as shown by how well it does on the mAP50-95 measure.

According to the results, YOLOV8 may be a little more accurate, but YOLOV5 is a good choice for more users because it stays the same at different IoU levels. It is important for people who want to use these technologies in the real world to have a deep knowledge of each model's strengths and weaknesses. The study can be used in many real-world situations. Data on rooftop detection and size estimate can make installing solar panels easier, which can help people become more energy independent and environmentally friendly. By adding this information to national grids, energy distribution can be improved because buildings will only get the power they need. This will lower their total reliance on grid power and may even allow them to export extra electricity. The data also helps the creation of micro-grids and community solar projects, which make it easier to distribute energy efficiently in smaller areas. Policymakers and city planners can use the data to make smart choices about zoning, building codes, and incentive programs, which will help cities grow in a way that is viable. Using green roofs and urban farming are two more ways to help the earth and make sure there is enough food for everyone. In the end, this thesis shows how important it is to use powerful deep learning models to protect the environment. Comparing how well YOLOV5 and YOLOV8 find rooftops and estimate their sizes, this study gives us useful information for improving the use of green energy, city planning, and efforts to protect the environment. The study shows how these technologies could lead to big steps forward in planning environmentally friendly structures, which would help make the future more sustainable.

Besides YOLOV5 and YOLOV8, the study could have looked at how well other deep learning models worked to make rooftop detection and size estimates even more accurate and reliable. Some possible models to think about are Faster R-CNN (Region-based Convolutional Neural Network), SSD (Single Shot Multibox Detector), and RetinaNet. These have all been used a lot in object detection and may offer different trade-offs between speed, accuracy, and stability at different Intersection over Union (IoU) thresholds. In future studies, this can be considered. Additionally, the deployment could be done more effectively and user friendly. Size calculation of the rooftop areas could be done automatically instead of providing information manually.

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