Project Solaris: Automated Progress Tracking of Solar Farms via Deep Learning

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Abstract. Solar energy has grown to become a key player for renewable energy in Malaysia poised for growth. The inherent issue that has come with such growth is the need to keep track of solar farm development. A fractured understanding of progress causes stakeholders being unable to make decisions with accurate information due to the manual tendencies hindering progress. Solving this issue no doubt can empower stakeholders with up-to-date information allowing for more decision making to be made early on, ensuring efficiencies are maintained. This study aims at automating the progress tracking of solar farms projects using deep learning. A seamless progress tracking ecosystem is developed by integrating deep learning with data visualization on a web-geo platform. The solution involves taking advantage of satellite imaging processing, image segmentation, data visualization techniques and data automation. This allows stakeholders to simplify the progress tracking and gain actionable insight without the need to visit farms physically. Ensuring this approach can revolutionize solar farm development tracking in Malaysia and transforming the decision-making process in its entirety moving forward.

Keywords: API, CNN, Deep learning (DL), Solar energy, KPI, MLOps, tracking system

1 Introduction

Malaysia's solar industry has seen rapid growth yearly, with many analysts poising solar as the next step for sustainable energy moving forward (Ghosn, Zreik, Awad, & Karouni, 2024). Today it has grown to 17% solar capacity when compared to earlier in 2019. As such it is imperative that solar farm development is done quickly and efficiently in order for the country to reach its goal of power mix of 70% by 2050 (Vercoe, 2023). To control the rapid growth and ensure achieving the goal, reporting the solar farms projects' progress for the stakeholders is crucial. Rather than manually dealing with the repetition of solar farms' data gathering, cleaning, analysis, a machine learning based solution can help to cut back on time wasted on the menial and provide insights for decision making.

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The current methodology of insight gathering is too time consuming and labor intensive. Requiring manual data preparation, followed by further preprocessing leading to slower visualization of overall progress greatly stifling the decision-making process. While current insight is still acceptable, it does not provide a comprehensive overview of key measurable key performance indicators (KPIs) (Abburu & Golla, 2015; Amini, Saber, Rabiei-Dastjerdi, & Homayouni, 2022; Ouchra, Belangour, & Erraissi, 2023). The lack of a centralized point for all stakeholders to seek information hinders progress due to the varying nature of understanding that can occur. More involved stakeholders may be well versed in the project's progress while others may struggle to know even basic details.

Kyriakos and Vavalis (2023) examined how satellite data and deep learning can serve businesses, particularly emphasizing the demand for straightforward, interpretable data solutions. This reflects the importance of simplicity and accessibility in data insights, which are crucial for effective business decision-making. Based on the insights from the article by Kyriakos and Vavalis (2023), the use of satellite data has become instrumental in insight gathering for businesses. In addition, Araujo, Kalinowski, Endler, and Calefato (2024) presented a detailed examination of Machine Learning Operations (MLOps), introducing nine guiding principles, including automation, reproducibility, and feedback loops. These principles collectively support robust, scalable, and collaborative ML workflows, underscoring the necessity of organized and iterative processes in successful ML project deployment and maintenance.

Golovko et al. (2017) explored the application of convolutional neural networks (CNNs) to detect solar photovoltaic (PV) panels from satellite imagery. The authors addressed a growing need to identify and monitor PV installations, which is crucial for energy planning, infrastructure management, and assessing renewable energy adoption. Methods for improving model robustness, such as data augmentation and fine-tuning the CNN architecture to ensure reliable performance across diverse environmental settings were discussed. However, the findings underscore the importance of advanced machine learning techniques in managing renewable energy resources through efficient and scalable satellite data analysis.

In addition, integrating, reporting and presenting the machine learning model outcomes on a web-based dashboard, make it simple for stakeholder to access the information and get insights timely. Shamat, Sulaiman, and Sinpang (2017) highlighted simplicity in design, advocating for intuitive and visually coherent webpages that present information concisely. Their approach is rooted in user experience (UX) design principles, focusing on intuitive navigation and iconography to ensure clarity and ease of access for users. Table 1 summarises the most related studies.

Table 1: Key related studies

Article	Main Idea
Kyriakos and Vavalis (2023)	- Use of satellite data and deep learning in providing insight to businesses. - Demand for simple and easy to understand environment to leverage data gained.

Araujo et al. (2024)	- Comprehensive overview of Machine Learning Operations (MLOps). - Identifies nine principles for effective MLOps: Automation (CI/CD), workflow orchestration, reproducibility, versioning, collaboration, continuous training, metadata tracking, monitoring, and feedback loops.
Shamat et al. (2017)	- Simplicity is king, everything should be simple but not basic - Transitions and pages, the visual treatment of webpages and positions of iconography. - Does the webpage provide information briefly and intuitively shows options to user.
Golovko et al. (2017)	- address a growing need to identify and monitor PV installations, which is crucial for energy planning, infrastructure management, and assessing renewable energy adoption. - discuss methods for improving model robustness, such as data augmentation and fine-tuning the CNN architecture to ensure reliable performance across diverse environmental settings.
Malof, Hou, Collins, Bradbury, and Newell (2015)	- Calculating estimated power capacity via the array of panels detected from satellite images using machine learning.

Based on the insights from the article by Kyriakos and Vavalis (2023), the use of satellite data has become instrumental in insight gathering for businesses. However, the shift in the market has brought about a demand for simple and easy-to-understand explanation of insights mined rather than complex projections and numbers. Its inherent wide availability allows for a large quantity of data to be collected and leveraged by systems allowing for better interpretation of the results. Key variables most sought after in regard to solar farm progress tracking are estimated completion time, solar panel changes, area changes and estimated time taken. These metrics allow for better tracking of solar farms for project managers.

Malof et al. (2015) tested the rooftop PV feasibility detecting via satellite imagery in the United States. The aim was to calculate estimated power capacity via the array of panels found, yielding a scalable and fast method for rooftop PV estimations. This study has taken the fundamentals in (Malof et al., 2015) further by leveraging satellite imagery to analyze the progression of solar farm development. Detecting each panel's installation and keeping track of overall changes leads to detailed breakdown of progression from project start to finish. It empowers users with a dedicated system of project management of solar farms. In addition, producing a transparent solution in keeping track of the progression of each site, packaging insights in an easy-to-follow format with removing a major caveat of utilizing satellite imaging helps to make the option a more attractive system which takes advantage of a fast scalable solution that can be utilized in tracking solar farms throughout the country. The simplified nature would also provide various stakeholders invested in the project progress of solar farms informing them of changes happening. The algorithm utilizes machine learning fundamentals as it is drilled on how to identify solar panels in satellite images before creating outputting the results.

Accordingly, this study's primary goal is to develop a prototype project management dashboard, Project Solaris, which utilizes deep learning to produce actionable insights

shown on a web visualization via a PowerBI dashboard. The aim is to achieve accuracy of more than the base line of 90% (Deepthi, Sandeep, & Suresh, 2021). Basically, Project Solaris problem scenario is how to automate solar farm development tracking, covering the main manual dependencies that currently exist such as counting of solar panel installed and ongoing and projections of completion time. With the ultimate goal of automating a majority of the work, leaving only the decision making to users reducing work fatigue and redundant tasks.

2 Methodology

The project is comprised of three key areas built upon and merged into a single seamless system. Beginning with a deep learning model that processes the satellite image of a solar farm. A visualization that converts output data by the model into actionable insight via easy-to-understand KPIs. Centralized in a web-geo platform for all users to access the updates easily and timely. Taking full advantage of deep learning, the research's goal is to take this idea to the prototype stage to test feasibility and develop an MVP, Minimum Viable Product. To assist in the development, Machine Learning Operations (MLOps) is chosen as the development framework of Project Solaris. The decision was made due to the framework being seen as an extension of DevOps that is improved upon to include projects that revolve around deep learning rather than solely focusing on software development. Its focus on continuous deployment allows a more robust automated deployment pipeline, which would increase the efficiency and frequency of deployments.

MLOps is a framework designed to streamline and improve the lifecycles of deep learning models and projects. It covers everything from design, to development, to integration, and continuous improvement ensuring stability. Figure 1 showcases the framework as a predominantly machine-learning function which at its core aims to streamline the process of taking ML models to market. With deep learning requiring repetition and training, this is the most difficult aspect of the entire project

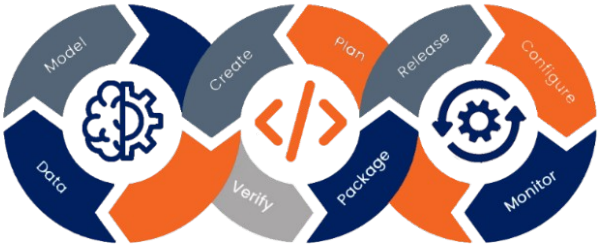

Fig 1. Chosen Framework Machine Learning Operations (MLOPS)

Adoption of MLOps yields several benefits, including improved efficiency due to streamlined deployment process of ML models, enhanced scalability across different projects and teams, better reproducibility due to practices such as versioning, and

automation of tasks. However, much like any project an inherent challenge of MLOps projects is its dependency on repetition and training, being the most difficult aspect. Regardless of the benefits reaped from the principles of automation, collaboration, reproducibility and versioning are all extremely useful in the long-term.

2.1 Requirement Gathering

To further expand the reasoning behind adoption of MLOps, its use allows significant reduction in the number of manual errors. Through automation of trivial tasks, deployment and monitoring of ML models, continuous deployment allows for a more robust automated deployment pipeline, which increases the efficiency and frequency of deployments. MLOps being better suited for bigger projects such as solar farm tracking due to frequent deployments having better utilization of version control due to multiple projects ongoing beginning and ending (Araujo et al., 2024).

While web development is typically associated with this framework, a mixture of MLOps principles and web design was chosen instead to emphasis the importance of user interface design in facilitating interactions and engagement on web applications. Based on the work conducted focusing on user input and output, it is essential the website's design promotes engagement and interest, which is crucial for encouraging users to upload images and interact with the image analytics features effectively and simply (Shamat et al., 2017).

Similarly, it is important to understand how the key metrics typically associated with solar farm tracking are used by various stakeholders. Verstatile tools such as PowerBI can be used in such instances where large amounts of data need to be refreshed in a set time periodically showcasing progress. Consequently, the primary focus of Project Solaris is to tackle the manual process of solar farm progress tracking. Leveraging deep learning and data visualization to both automate and simplify tracking.

2.2 Analysis and Design

In order to achieve the laid-out focus, the general flow aims to simplify progress tracking to one single continuous flow. Beginning with users uploading the latest satellite image of the solar farm on the website. Whereby it is processed by the algorithm into data comprising of key indicators such as progress in percentages and solar panel changes. The proposed centralized web-geo platform aims to empower users with easy-to-follow insight in regards to progress tracking of solar farms. Mainly in the form of easy-to-understand dashboards that keep track of key metrics. Navigation is key to the project, as effective design elements need to convey what users can do as well as maintaining usability for all (Garett, Chiu, Zhang, & Young, 2016).

This innovative approach of simplifying the current business process flow as seen in Figure 2, shows the only real manual process coming in image upload. While the deep learning algorithm processes the satellite image before outputting it in the form of two visualizations showing the main and simplified data for users to view.

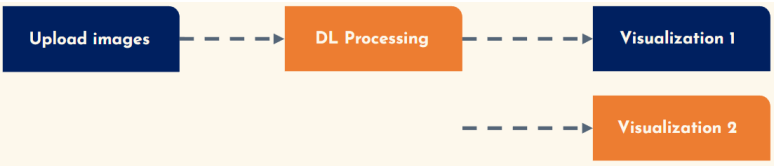

Fig 2. Business Process Flow

As seen in the design phase, Figure 3 details the moving parts of Project Solaris, the front end of the project primarily on the user experience, while the back end handles all analysis.

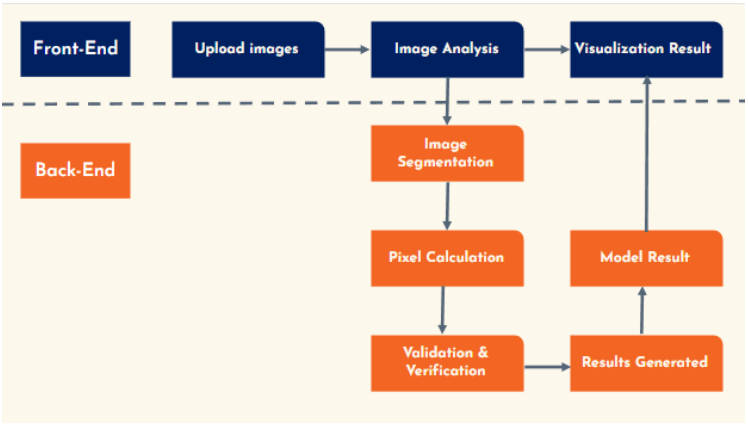

Fig 3. System Overview

Accordingly, multiple processes proceed one after a single upload as the idealized system works in unison to deliver the results. Analysis via the system aims to take place behind the scenes as the satellite image is processed, before imported into the dashboard and updated with the latest data available, allowing the user to view the latest progress of a chosen solar farm with frequently automated refreshes.

2.3 Implementation and Development

To ensure the project progresses smoothly and efficiently, we implement several practices from the MLOps framework. Automation plays a large role in this project, with automated pipelines that preprocess, transform, and analyze input images that are then displayed onto the website with insights and a predicted completion date based on data. Versioning and reproducibility are paramount for keeping track of different versions of our deep learning models and code, ensuring that they can be rolled back to previous versions in the case of issues and avoiding major setbacks. GitHub can be used to track ML model and website code versioning;

Measurable Variables: the number of panels installed, area covered, capacity installed (in kW), and time taken per panel installation.

Dimension Variables: These might include different project sites, teams or crews handling the installations, and stages of installation (e.g., planning, executing, monitoring).

The foundation of any deep learning model is the quality and comprehensiveness of the training data. A detailed and well-curated dataset was sourced from Kaggle. The dataset is pivotal for training our model, ensuring it can accurately classify satellite images to identify solar panels. The raw images in this dataset are predominantly 5000x5000 pixels, with a resolution of 0.3 meters per pixel. This high resolution ensures that even the smallest solar panels are visible and identifiable, providing the model with detailed visual information to learn from. The large image size and high resolution facilitate the detection of fine details, which is essential for distinguishing solar panels as seen in Figure 4.

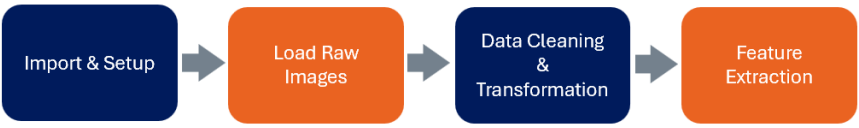

Fig 4. Training Process Flow

To facilitate the ease of use in the deep learning model, the satellite images are preprocessed to ensure data is reliable and consistent as to ensure high accuracy.

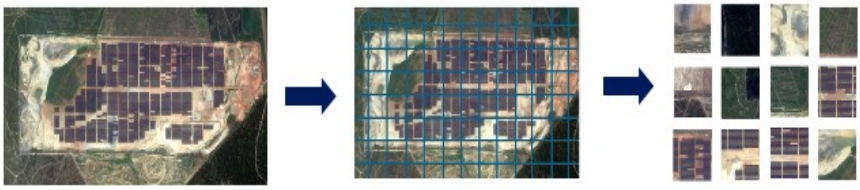

Fig 5. Satellite Images Data Preprocessing

Some steps taken in order to better preprocess the data of satellite images can be seen in Figure 6 where the full-scale satellite images are broken down via patch extraction. Before further analyzing with deep learning is done, some data preprocessing practices are done in order to ensure data used is clean and transformative.

1. Cropping & Resizing:

Objective: Standardize the input size for CNN.

Process: Each satellite image is resized to a uniform dimension, typically 256x256 pixels. Standardization is critical to consistency in the input dimensions, which is a prerequisite for feeding images into a CNN improving learning patterns more efferently.

2. Noise Reduction:

Objective: Enhance image clarity by removing noise.

Process: Techniques such as Gaussian blur and median filtering are applied to the images. Gaussian blur reduces high-frequency noise by smoothing the image, while median filtering preserves edges by reducing impulsive noise highlighting the relevant features of the images while minimizing distortions.

3. Brightness and Contrast Adjustment:

Objective: Improve visibility and highlight features.
Process: Adjustments are made using histogram equalization and CLAHE (Contrast Limited Adaptive Histogram Equalization). Histogram equalization redistributes the intensity values to enhance global contrast, making the overall image brighter and more detailed. CLAHE, on the other hand, enhances local contrast, making subtle details more visible. Ensuring the model can distinguish solar panels.

4. Geometric Corrections:

Objective: Correct distortions and align images.
Process: Geometric transformations such as rotations, translations, and perspective adjustments are performed to correct any distortions and align the images properly. Ensures that the features within the images are correctly oriented, essential for accurate detection and classification. Proper alignment helps the model to consistently identify better.

5. Normalization:

Objective: Standardize the image intensity levels.
Process: The pixel values of the images are scaled to a common range, typically [0, 1] or [-1, 1]. Normalization reduces the variability caused by different lighting conditions and ensures that all images have similar intensity distributions. Crucial for improving the convergence of the neural network.

6. Data Augmentation:

Objective: Enhance robustness and generalization.
Process: Data augmentation techniques are applied to artificially increase the diversity of the training dataset. These include rotations, horizontal and vertical flipping, zooming in and out, translations, and random cropping. By creating multiple augmented versions of each image, the model is exposed to a wider variety of scenarios and configurations, preventing overfitting and improving its ability to generalize to unseen data.

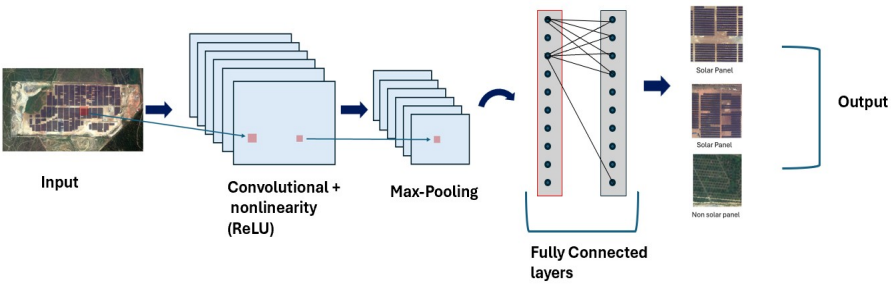

Fig 6. CNN Model Development Flow

Figure 6 displays an example of the flow of input data (Satellite Images) going through the three CNN layers and producing the output data (Classified Components). CNN as tested by Simonyan and Zisserman (2014) concluded that is very adaptable to large-scale images such as solar farm satellite images. The first component, Convolutional Layers, are the core building block of CNN, used to detect features in the input image such as patterns, textures and edges. These layers work by having filters, also known as kernels, are small matrices that slide across each image and calculate the dot product between the filters and a local region of the input image; This produces a feature map, which is a grid of values that represent the existence of certain features that are detected by the filters as the input image is put through them.

By applying multiple filters to an input image, multiple feature maps can be generated, each identifying a different feature. All 3 layers work in tandem to learn from, process, and classify features from input images. This makes CNNs effective for image analysis in Project Solaris. CNNs' properties of local connectivity and weight sharing significantly reduces the number of parameters and increases processing speed, making them highly efficient for image processing tasks such as our usage of satellite imaging (Zhang et al., 2019).

To track the build progress of the solar panel plant, we utilize pixel calculation. This process involves counting the number of pixels that contain a solar panel and comparing it to the number of pixels in the planned build area for the solar power plant.

After the CNN model is done classifying the satellite images, pixel calculation is used to count the total number of pixels of complete and incomplete solar panels, and we can determine the proportion of the area that has not been developed (see Figure 7). This approach allows for precise monitoring and measuring of the construction progress over time, which aids the project managers in accurately determining build status and making informed decisions to better maintain progress.

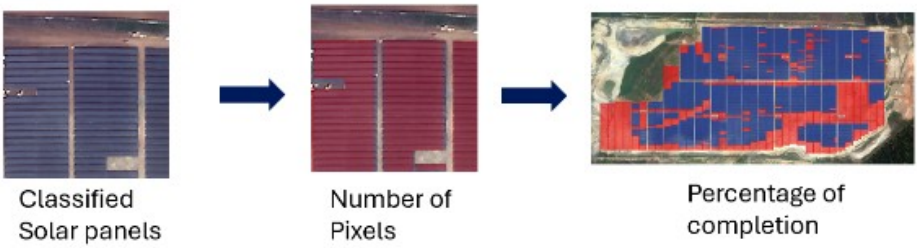

Fig 7. CNN Segmentation Process

Segmentation process involves the following steps:

*1. Loading the Segmentation Map:*The "segmentation_map" is a 2D numpy array that represents the classified pixels from the CNN model. In this example, "1" represents built solar panels, and "0" represents unbuilt areas.

2. Total Pixels Calculation:"total_pixels" is the total number of pixels in the segmentation map, which corresponds to the total planned build area.

3. Counting Built Pixels: "built_pixels" is calculated by summing the number of pixels classified as "1" (built solar panels).

4. Percentage Calculation: The percentage of completion is calculated by dividing "built_pixels" by "total_pixels" and then multiplying by 100.

Assume each pixel in the image represents 1 square meter, if the total planned build area is 10,000 square meters, and the model identifies 3,000 pixels as built solar panels: **Percentage of Completion = (3000/1000) x 100 = 30%**

Web Development also plays a large part in our proposed Project Solaris as the goal is to develop and easy-to-use centralized web-geo platform. The tool primarily used in web development is Visual Studio Code as its flexibility and utilization of Javascript allows for HTML and CSS the main languages in web development is fully utilized. The main webpages consist in totality as follows:

- Landing Page, where users are shown ongoing projects
- Overview Page, where data is simplified to its essential information for stakeholders
- Dashboard Page, showing all the KPIs of the solar farm development
- Upload Page, where users will upload their satellite images.

The final piece of the puzzle of the proposed web-geo platform is the data visualization via PowerBI. PowerBI is the chosen data visualization tool due to its ability to be linked with a shared folder allowing for new data to be scrubbed daily. Automating data refreshes and thus removing another manual step typically found in the previous methodology iteration. Delivering a seamless user experience from start to finish about progress tracking of solar farms.

2.4 Testing & Integration

Project Solaris since its inception has come with various challenges but after a variety of iteration it has achieved its most functional state as a Minimum Viable Product ready for further improvement. Allowing users to upload various images (satellite) with ease and store them in a shared folder. Integrating all three aspects of Project Solaris.

During implementation of our solar panel detection and segmentation project, we experimented with various deep learning architectures to determine the most effective one. Various tests were done to ensure results provided were accurate. Metrics such as the validation score, precision, recall, F1 Score and K-Fold Accuracy are used to test three CNN models namely, InceptionV3, ResNet50 and MobileNet.

Initially a hybrid model was considered, implementing both the image classification and segmentation to detect and segment solar panels simultaneously. However, we decided to proceed with a segmentation-only strategy, as the former proved issue-

ridden. We chose to use the U-Net model with a VGG16 backbone. We experimented with the InceptionV3 model, a popular convolutional neural network that distinguishes itself in high efficiency in image classification. The network uses multiple convolutions with different window sizes to capture different features at multiple scales.

In our experiments, the model demonstrated high results – the validation accuracy has reached the mark of 0.94. More specifically, the precision was at its highest, detected to be 0.91, and the recall was 0.99, resulting in an F1-Score of 0.95. The model was also able to identify the solar panels' regions correctly at an 85% K-Fold accuracy. However, further use required a second neural network to perform the segmentation, which increased the system's complexity. Furthermore, our tests demonstrated that there could be cases when the InceptionV3 model would not notice all relevant regions, undermining the effectiveness of segmentation.

ResNet50 was also tested, as another powerful convolutional neural network. The model prevents the vanishing gradient problem by using residual connections and has therefore proven to be very efficient and accurate. However, it did not perform well in our case – the validation accuracy was only 0.46, while the precision and recall were lower, as well. F1-Score was 0.16, and, moreover, the K-Fold accuracy was only 60%. Overall, we can conclude that ResNet50 was not the best fit for our task of solar panels detection, since we required high precision in our results.

We also examined MobileNet, a CNN optimized for lightweight applications on mobile and embedded vision devices. In terms of efficiency, this model offered decent results but did not excel much beyond this. Its validation accuracy was 0.52, and it demonstrated the same precision, recall, and F1-Score of 0.52. Meanwhile, its K-Fold accuracy was 75%. However, even when the model delivered only average results, we did not consider it for implementation. The primary reason for such a decision was the complexity that would accompany the integration of such a model with a segmentation approach it did not completely satisfy our emerging requirements. Pushing Inception V3 as the main deep learning model for Project Solaris.

3 Results

The end goal was to create a deep learning model that detects and segments solar panels from satellite images. At first, we started by breaking the task down into two parts: one to classify if a region comprises potential solar panels using a classification model, and another to segment these regions. However, after lots of experiments, we realized that doing segmentation directly without first classifying is not only easier but also performs better and faster than the earlier method. In the following section, these are some images that were taken to showcase our deep learning model.

Metrics such as the validation score, precision, recall, F1 Score and K-Fold Accuracy showed InceptionV3 as the superior model. As the model was developed with mutli-scale processing and the ability to capture complex patterns in images such as solar panels (Szegedy et al., 2015).

	Metrics				
CNN Model	Validation/ Accuracy	Precision	Recall	F1-Score	K-Fold Accuracy (10-fold)
InceptionV3	0.94	0.91	0.99	0.95	85%
ResNet50	0.46	0.44	0.48	0.16	60%
MobileNet	0.52	0.52	0.52	0.51	75%

Fig 8. CNN Model Comparisons

These tests help improve the pixel-based segmentation in order to achieve similar results as seen by precursors with footprint extraction (Abujayyab et al., 2023).

In Figure 10, the original satellite image is on the left, and the segmented output of our model is on the right. The segmented image gives a clear distinction between solar panels and the environmental context. Such a level of precision is essential for applications that need tight visual-style analysis and precise area calculations. This particularly showed a very accurate segmentation model, especially with 2-stage fine-tuning using U-Net architecture and VGG16 encoder, that detected all solar panel locations, even at the minutest level.

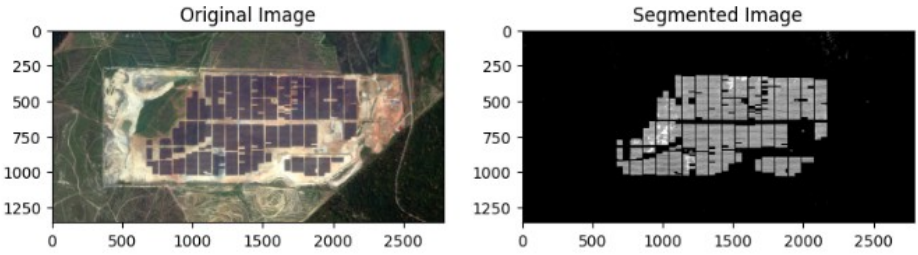

Fig 9. Finalized Segmentation Result

With a simplified website that centralizes access to data and satellite imagery. It sets the scene for users with the help of an integrated PowerBI dashboard, the Overview Page gives users a rapid overview of the project's main KPIs. A thorough view of all pertinent data is provided by the Dashboard Page, facilitating in-depth analysis and insight. Lastly, the Upload Page makes it easier to submit TIFF files, which are thereafter kept in a database to guarantee that data is arranged in a methodical and user-friendly manner. Combined, these pages improve navigation and facilitate efficient image analysis by gathering and displaying information in an approachable way.

Users can upload TIFF files pertaining to specific sites and installed panel counts through the upload page of the website. An image's ID, name, and site detail are captured and recorded for image processing and analysis when files are uploaded and saved in a phpMyAdmin database.

A thorough PowerBI dashboard with all the information and visualizations required for in-depth analysis is featured on this page. In order to monitor progress and make

wise decisions, users can examine all pertinent metrics and insights. A PowerBI iframe embed link is used to embed the dashboard, enabling daily dashboard updates that help maintain the accuracy and consistency of the data.

The overview page (Figure 11) consists of a PowerBI dashboard displaying key information like Panels Left, Days Needed, and Completion Rate is integrated into the design of this website. It gives the users a fast overview of important project data so they can comprehend the project's state and direction more efficiently improving decision-making.

Fig 10. Dashboard Page

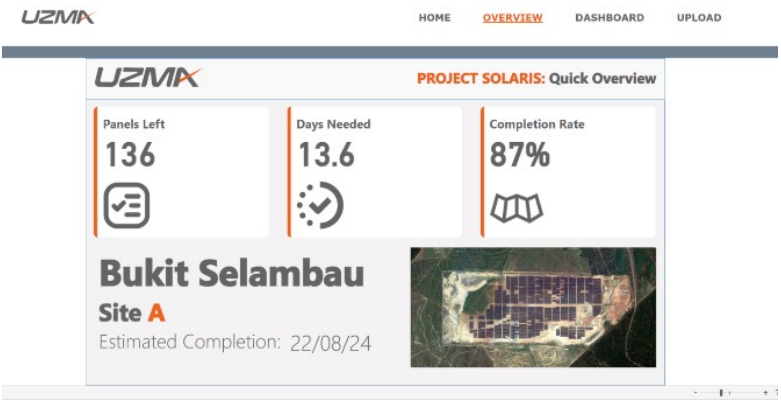

Fig 11. Overview Page

4 Implications

As solar continues to become the norm in the advancement of the energy industries, Uzma will no doubt be looking forward to more solar sites. With such prospects on the horizon, the proposed solution will no doubt be an invaluable tool. Having the

ability to analyse solar images and extracting actionable insights leveraging deep learning no doubt brings factors of convenience and accessibility to those involved.

A) Deep Learning Algorithm
With the emergence of artificial intelligence, it's no wonder many industries are beginning to adapt to the new powerful yet controversial medium. While deep learning is merely a subset of it, such a tool will no doubt bring a variety of benefits. Such benefits could be the simplification of such complex task, cutting down on the perceived difficulty and tools used.

B) Dashboard Visualization
Visualization of data plays a crucial role in breaking down data extracted from the images. As the ability to read into the insight will be the decision between making a mistake and making a swift decision to sort out any issues that may arise. Identifying and showcasing all progresses, timeline estimates, and percentages allows for better judgement overall.

C) Web-Geo Platform
Due to the lack of a centralized location used to store data pertaining to solar projects, a web-geo platform is no doubt the best solution moving forward.

5 Limitations and Future Work

Much like with any project development it is pivotal to make note of the limitations that occur when developing a project that enters the MVP stage. In our proposed solar management hub system, the main limitation we faced was the full integration of the deep learning algorithm into the web-geo platform. This is due to the inherent complexity with Uzma's own APIs and software integrations preventing us from fully completing integration in its entirety.

Another pitfall we faced was the insufficient training data received by Uzma as we only got about two digits worth of actual site images. While still helpful prevented us from reaching an even better accuracy rating at the end and having relied on clean data after being preprocessed from Kaggle. Similarly training time also take a large limitation time as the cost of running Google Collab overnight proved difficult as the equipment we used while good was not the most optimal of setups for deep learning development, with increasing cost in memberships for better tools and time restraints.

Taking into account the current limitations listed for the future work we would better prepare the training of the deep learning algorithm by getting at least three digits worth of training data. As with more data the model will output and overall higher accuracy providing clean reliable data.

6 Conclusion

As mentioned, the goal of this research project was to develop an automated progress tracking solution, empowering users with actionable insight on solar farm

development. Project Solaris, a web-geo platform that leverages deep learning in order to process satellite images of solar farms into actionable insight in the form of a visualization. The system utilizes deep learning in order to process the progress of solar farms via satellite images, pixel calculation is done tracking differences in panels installed and overall percentage. This innovative approach allows for accurate and readily available data to be output in a short time before being uploaded into a dashboard for better understanding of overall progress. All centralized in a single location for ease of access to the various stakeholders invested in solar farm development. With our aspirations for Project Solaris to transform the solar industry and progress tracking of solar farm development throughout Malaysia. Ensuring stakeholders are able to make informed decisions frequently with transparent progress showcased.

To conclude, the research done on automating progress tracking of solar farm development, leveraging deep learning and visualization has the potential widespread adoptability. Empowering users and advancing the solar industry in Malaysia by automating a significant process of development while demonstrating the transformative capabilities of technology utilized in solar farm development.

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