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SolarIQ – AI-Powered Industrial Rooftop Solar Lead Generation

Vaishali Rajput[1], Sumedh Malode[2], Sujal Tawale[3], Samruddhi Wayal[4], Soyam Maykar[5] and Ayush Tangde[6]
[1-6]Department of Artificial Intelligence & Data Science, Vishwakarma Institute of Technology, Pune- 411037, Maharashtra, India
Email: sujal.tawale23@vit.edu Sujal Tawale

***Abstract*— Industrial rooftop solar adoption is expanding globally and identifying technically and economically but viable rooftops remains a manual, time-consuming and error-prone process. SolarIQ is an AIML and GIS-driven platform designed to automate the end-to-end workflow of industrial rooftop solar lead generation. This system uses satellite imagery and a U-Net–based segmentation model for the detection of industrial rooftops and exclude existing solar installations. Furthermore rooftop characterization is performed using PyPVRoof to compute tilt, azimuth, usable surface area and potential installation capacity. Solar energy simulation is carried out using pvlib to estimate annual energy yield, cost savings and CO_2 emission reduction. To convert technical insights into actionable business leads, SolarIQ integrates automated decision-maker data enrichment using corporate registries and LinkedIn APIs. All the further results are presented through a cloud-deployed dashboard powered by FastAPI, PostgreSQL, PostGIS, Streamlit and React which enables real-time lead management. By integrating rooftop detection, solar estimation and business intelligence into a unified platform, SolarIQ significantly reduces the solar sales cycle and enhances the scalability of industrial solar deployment.**

***Keywords*— AI rooftop detection, U-Net segmentation, satellite imagery analysis, solar potential estimation, pvlib, PyPVRoof, GIS, Geospatial processing.**

I. Introduction

The international necessity to switch to renewable energy sources has become more urgent due to the fact that we are observing the increase in energy requirements, the aggravation of environmental degradation, and the rise of economic feasibility of clean technologies. Of all the renewable alternatives, solar, in particular, industrial rooftop solar, has emerged as a very scalable and cost-efficient method of reducing carbon emissions and achieving those long-term sustainability goals that people are always discussing. Despite its enormous potential, the actual implementation of industrial rooftop solar continued to run into enormous obstacles, especially in the initial phases when you are scraping through roofs to identify the correct ones and transform those opportunities into high-quality sale leads. The conventional methods of Solar EPCs, consultants, financiers, and energy auditors are mostly manual and unstandardized and depend on the subjective judgment of experts. Such restrictions only lead to inefficiencies, increase the cost of operation, slow sales and eventually delay the transition to solar energy globally.

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Concerning the key problem, it is a nightmare to identify which rooftops of industries might possibly contain PV panels. The EPC crew are in most instances simply scrolling through archived satellite images, conducting field inspections manually, or searching through out-of-date datasets that only provide the general outlines of the building, but not the details of the roofs. Such datasets do not contain any of the nitty-gritty data, such as the shape of the roof, shadows, tilt, azimuth, the surface you can actually use, every such variable is the key to determining how much solar you can actually produce. And these standard rooftop data sets do not indicate the presence of panels on a building, so you may end up classifying a roof as a potential one when it is already covered, disrupting your work and wasting time. All this makes it difficult to determine the actual economic viability of a location by the companies, slows decision making, and eventually leads to poor lead qualification.

In addition to the technological aspect, there is also a huge issue of connecting the feasibility analysis directly to business actionable intelligence. And once you find a roof and calculate its solar potential, the EPCs must still go searching through corporate registries, company websites, and LinkedIn-like networks to locate the appropriate stakeholders, decision makers and contact information. This division process brings a great deal of tension between the technical evaluation and sales teams, and you cannot make an insight into a revenue within a short period. The fragmented workflow interrupts scalability and increases the cost per acquisition, particularly in an attempt to enter dense, high-volume industrial markets.

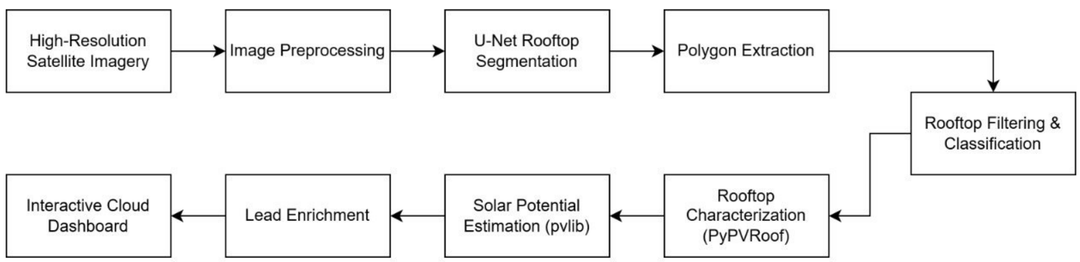

Fig 1. Overall System Architecture

In order to close these key gaps, the existence of SolarIQ is being marketed as a uni-friendly, AI-based geospatial analytics platform designed to automate the task of identifying industrial rooftops, calculating solar viability, and generating business leads. It uses deep-learning models, primarily U-Net to segment high-resolution satellite images and nail down the roof of an industrial building with relative solid precision. [1] Proposes a deep learning framework to estimate city-scale rooftop solar potential while considering roof superstructures using satellite imagery.[2] Uses multi-resolution remote sensing and deep learning to assess rooftop photovoltaic potential at a geospatial scale.

The system divides usable roof surfaces and stuff that covers them, such as shading or existing panels, to generate clean and reliable roof polygons, which you can then feed into more detailed tech analyses. This automation reduces the time required to complete the first scan by days to minutes, which is a massive achievement when it comes to conducting a large-scale study in industrial areas.

In addition to identifying roofs, SolarIQ is also connected to PyPVRoof to compute all the important roof measurements, which include the tilt, azimuth, and the real usable area of the roof. Those figures are essential to determine whether solar can fit there or not. Besides, it introduces pvlib, the industry standard library in solar, to calculate irradiance, annual energy production, carbon credits, cost savings, and projected ROI. [16] Introduces the pvlib Python library for modeling and simulating solar energy systems.The analytics provide EPCs, corporates and financiers with the data-driven insight they require to abandon the guesswork and make the most accurate possible decisions.

The thing is that what makes SolarIQ stand out of the common academic models and the free rooftop detection tools available is that it does not just automate lead enrichment. [13] Reviews remote sensing techniques for photovoltaic detection, applications, and future research directions. The platform scrapes major decision-maker data out of social sources, business registries and LinkedIn - and it returns complete organizational profiles, contact information, business types and the chain of command. In essence it makes those cold, technical evaluations leads that can actually be used to make sales or analyse the market. And you have a nice transition between seeing a roof and a prospect that is ready to go, both the engineering part and the business part of industrial solar.

The results are displayed on an interactive, cloud-based dashboard created with FastAPI, PostgreSQL with PostGIS and either Streamlit or React, depending on the stage in the deployment chain you are at. [8] Uses

LiDAR data and GIS techniques to assess rooftop solar energy potential accurately. It means that you can even see shapes of rooftops on live maps, filter prospects by economic or environmental indicators, export reports and follow actual lead pipelines in real-time. The entire design is modular such that it can be scaled well to allow you to expand across cities, states or countries as additional satellite data is received.[18] Presents a LiDAR-based method for predicting citywide rooftop solar energy potential.

Overall, SolarIQ is a single, integrated solution to the primary challenges in the uptake of industrial rooftop solar. The platform reduces the costs of acquiring solar by integrating AI-powered roof detection, realistic solar simulation, geospatial processing and automated business intelligence to shorten sales cycles and increase the overall scalability of deploying solar on an industrial scale. With this combination of innovative technologies, SolarIQ is actually contributing to accelerating the process of switching to renewable energy and achieving carbon-neutral targets in the world.

II. Materials and Methods

This particular section describes the materials and design required for the successful development of the particular proposed system. The system uses satellite imagery, a U-Net–based deep learning model for rooftop segmentation and geospatial tools such as GeoPandas and PostGIS for polygon processing. PyPVRoof and pvlib are applied to compute rooftop characteristics and simulate solar performance. A FastAPI backend with Streamlit/React frontend integrates the pipeline into a cloud-deployed dashboard for real-time lead generation.

A. System overview

SolarIQ is intended to be a complete end-to-end AI platform that automatically identifies, assesses, and qualifies industrial rooftops for solar installation. [19] Uses deep learning over aerial imagery for automated mapping of rooftop photovoltaic installations. The pipeline combines computer vision, geospatial analysis, solar performance analysis, and automated lead enrichment. The first step of the pipeline is the acquisition of satellite images, followed by rooftop detection via a U-Net segmentation model, which isolates the usable rooftop polygons while excluding areas with existing solar installations or obstructions. [17] Proposes the U-Net convolutional neural network architecture for accurate image segmentation.The polygons are then processed by PyPVRoof to determine rooftop tilt, azimuth, and usable area.

The subsequent step is the solar simulation with the help of pvlib for irradiance, annual energy production, CO2 reduction, and cost savings to assess the technical and economic viability of the installation of a solar PV system. After SolarIQ has identified a feasible rooftop, the organizational details and contact information of the decision-maker are automatically obtained through public registries and LinkedIn APIs, thus translating technical knowledge into sales-ready leads.

All processed output-rooftop polygons, performance estimates, financial analysis, and business data are presented through an interactive cloud-based dashboard developed using FastAPI, PostgreSQL/PostGIS, and Streamlit or React. [4] Presents a remote-sensing-based approach for estimating rooftop photovoltaic power production potential. This allows EPC firms, consultants, financiers, and corporates to analyze rooftops, compare possible installations, and update leads in real-time. SolarIQ integrates detection, simulation, geospatial intelligence, and business analysis into a single solution that will significantly lower the time required for lead generation and improve the scalability of industrial solar adoption.

B. Working principle

Image Acquisition

The basic concept of SolarIQ is to identify, survey, and map industrial rooftops and install solar panels on them. It is a combination of computer vision, map information, solar performance forecast, and even auto lead stuff. First, it captures images of the satellites and transports the U-Net model to isolate the rooftops that actually operate without considering the ones that are already covered or concealed by other objects. It subsequently transfers those shapes to PyPVRoof to get the tilt, azimuth and area which can be utilized.

[15] Estimates the potential of residential rooftop solar energy with spatial and energy modeling. It then runs pvlib to simulate the solar, and you get the variables of irradiance, annual energy output, CO 2 reduction, and money saved, to determine whether the system is technically and economically viable. [16] Presents the pvlib Python datalayer modeling and simulation of solar energy systems. After finding a good rooftop, SolarIQ pulls out company data and contact information of the decision-maker based on public records and LinkedIn APIs and converts all that nerd stuff into leads that are marketable. The polygons, energy forecast, cost and business analytics are all fined and displayed on a cloud-based dashboard created using FastAPI, PostgreSQL/PostGIS

and either Streamlit or React. That allows EPCs, consultants, investors and corporate individuals to search roofs, compare, and keep leads updated in real time. Essentially, SolarIQ is a bundle of detection, simulation, geospatial smarts and financial analysis that shortens the lead-gen time and eases the deployment of industrial solar greatly. [7] Predict rooftop solar energy potential in high-density urban regions with satellite and space-based data.

It starts with the snatching of high-resolution satellite images, which are the primary input in the analysis of the rooftops. These pictures are provided by the best suppliers of satellites, then they are pre-processed, georeferenced, normalized and sharpened in such a way that the map data appears in the correct location.[1] Proposes a deep learning framework to estimate city-scale rooftop solar potential while considering roof superstructures using satellite imagery .The slightest deviation can cause roof detection to go awry and hence cleaning and standardizing everything is extremely important. The vision pipeline is compatible with clean, homogenous images and maintains low noise levels, which is essential to make reliable predictions of rooftop information and solid predictions of solar potential in the future.[10] Introduces a methodology for rooftop solar potential assessment using rooftop extraction from remote sensing imagery.

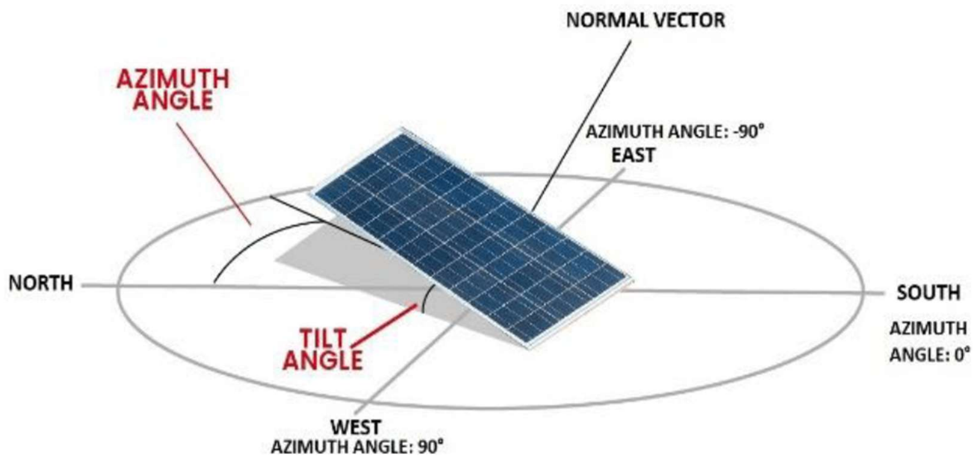

Figure 2: Illustration of Solar Panel Tilt and Azimuth Angles

Rooftop Detection

The system have a U-Net segmentation model which is trained to identify roofs of buildings in satellite images. [17] Proposes the U-Net convolutional neural network architecture for accurate image segmentation. It scans pixel patterns and extracts roofs and other objects such as trees, roads and fields. When it is complete, the output mask becomes the polygon boundaries which trace the edges of each roof. This computerized process replaces the manual spotting process, reduces the human error factor, and simplifies the entire transaction. [12] Develops an automated system for rooftop solar panel detection and power estimation using remote sensing. The encoder-decoder architecture allows the model to extract high-level and low-level features, which is why it is very proficient at identifying tricky roofs in industrial areas.[6] Develops automatic color-based techniques to detect photovoltaic panels in aerial images.[11] Proposes a deep active learning approach for global-scale rooftop photovoltaic detection.

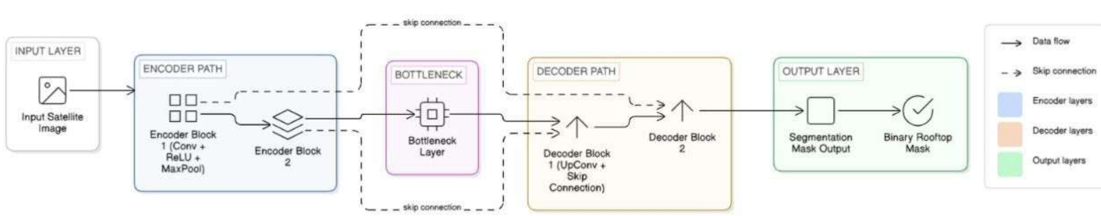

Figure 3: U-Net Architecture for Satellite Image–Based Rooftop Segmentation

Rooftop Filtering and Classification.

Once the polygons are prepared, a quality check is done to eliminate roofs that are not capable of supporting panels. It removes roofs already with panels with a second classifier which identifies common panel textures.[14] Uses GIS and remote sensing to identify suitable sites for solar panel installation. It also removes shaded roofs, HVAC rigs, trees and oddly shaped buildings that reduce sun exposure. Roofs that pass these tests are only advanced. Such additional checks increase the precision of the final list of leads, providing EPCs and investors with only the high-value opportunities.[19] Uses deep learning over aerial imagery for automated mapping of rooftop photovoltaic installations.

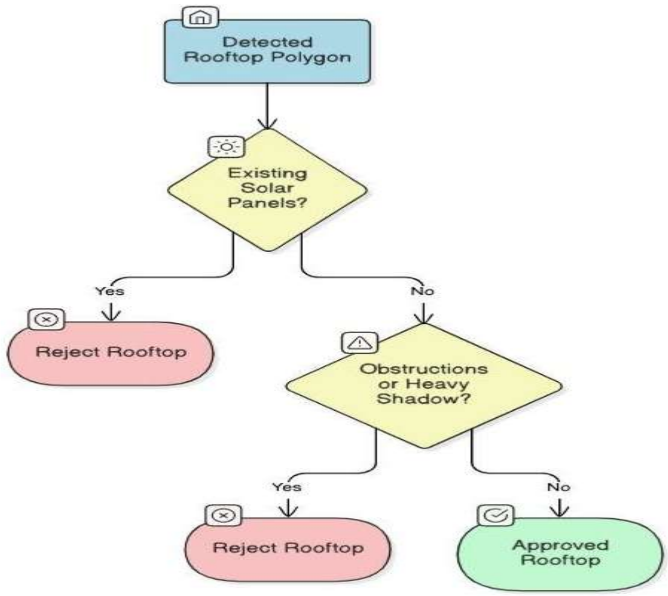

Fig 4.Rooftop Filtering Logic

Rooftop Characterization

PyPVRoof is a program that calculates the key numbers required to calculate solar by taking all accepted roof polygons. It calculates tilt using the elevation variation, azimuth using the directional information and the useful area by removing the bad points. These figures have a direct impact on the effectiveness and sustainability of a solar installation. Basic outlines can be converted into detailed 3D aware surface profiles, which allows us to model panel placement more realistically. Concisely, this step provides the technical backbone with the appropriate metrics that are input to energy and cost estimates.

Solar Potential Estimation

Having the roof data, pvlib comes in to estimate the solar potential of each site. It draws in tilt, azimuth, position, and local sun data to emulate system operation. It provides annual energy output, estimated CO 2 savings and financial results such as cost savings and ROI. pvlib provides good projections since it combines real-world weather with PV system specifications. This last step transforms raw roof numbers into practical, real information that can be used to determine whether a project is going to be profitable.[9] Applies GIS and photogrammetry methods to evaluate photovoltaic potential on flat rooftops.

Lead Enrichment Process

The system then provides a business makeover to each rooftop lead after crunching the technical data through automated enrichment. It scrapes company profiles, industry tags, and contacts of decision-makers off official registries, online databases, and LinkedIn APIs. Converting a bare solar potential to a complete business lead reduces the sales outreach time of EPCs by half. As it gets enriched, all valid rooftops are matched with the appropriate org information, which allows solar companies to strike the appropriate stakeholders directly. This move will close the gap between the feasibility and commercial interaction, and the entire pipeline can be used throughout.

System Integration Process.

The entire process is based on fully integrated process wherein the CV, geospatial analysis, performance modeling as well as lead enrichment is being reinforcing. The rooftops are recognized, filtrated, described and estimated in a pipeline that is automatically executed by FastAPI services. Everything is stored within the spatially enabled PostgreSQL-PostGIS database that causes it to be geolocation spot-on. The modular architecture will see us reach expansive geographical destinations and be real-time. This integration ensures that there is consistency in the data, loss minimization and makes the platform spew out the optimal solar insights within minutes.

Dashboard Visualization

The final result is thrown into a cloud-based dashboard that was initially an implementation in Streamlit but later on a production application in React. The dashboard gives you a map that you can interact with to scan caught roof tops, can view solar potential statistics and get enriched lead data. Geospatial layers, charts, and tables will help you in the analysis of performance estimates and comparison of the opportunities in various regions. This interface of ease of use simplifies complicated backend mathematics and converts it into simple easy-to-use interface which is usable by EPCs, consultants, and financiers. It makes sure that it is clear, visible and understandable by everyone.

C. Training the Model

In this section of the project, this system collected an enormous amount of satellite images of several industrial sites and performed the usual pre-processing operations i.e. cleaning the data, normalization of the values of the pixels, etc. Such shots have rooftops of every shape, material, color with environmental problems such as shadows, flora and other atmospheric factors. The images were then hand marked to produce pixel based masks which distinguish between the rooftops and all other features. This provides the network with a strong monitored learning signal on parting. So, here this system has also included data augmentation to enhance the robustness of the model. The system has rotated, scaled, changed the brightness and contrast. The next step, which involved labeling the data, led to the establishment of a training, validation and test set to make sure that the system could retain the balance of the training and the objective of an evaluation. On such difficult industrial layouts , training of a U-Net using a batch size of 16 and 60 epochs, Adam optimizer and Dice loss and binary cross-entropy to squeeze the best segmentation results. After the deployment of the segmentation model, a second classifier to detect solar panels as well as other rooftop items is developed. This classifier had been trained on a labeled dataset which included solar installations, mechanical structures, shadows and plain inaccessible places. The result of the softmax was the probability of the classes which allowed me to filter bad rooftops with accuracy. Here the system has followed the F1, accuracy, and precision of the training and selected the most suitable checking of the validation of each model. Validation-selected-then models performed best and were scaled into the SolarIQ pipeline to provide us with a strong scalable rooftop detector system which can operate in large geographical areas.

D. Testing the Model

The tested system was strict to the segmentation and classification nets at the end of the training phase with another set of new satellite images which the models had never encountered. These test images were an amalgamation of industrial buildings of another level of lighting and texture, and it assisted in determining whether the network is generalizing to real world scenes. The predictions were compared to the ground-truth masks and the system calculated the IoU, the precision, the recall, the F1, the boundary-accuracy to measure the performanceFailure cases, including the misclassification of metallic rooftops, the presence of heavy shadows, and cluttered industrial environments, were systematically analyzed to identify areas requiring further refinement. The insights derived from offline experimentation were subsequently deployed in a cloud-based environment, enabling large-scale inference across real-world industrial regions. Incoming satellite tiles were continuously updated, allowing for real-time monitoring of detection accuracy, processing latency, and the geometric quality of the generated rooftop polygons. To ensure the reliability of rooftop suitability outputs, these quantitative metrics were validated against on-site inspections and feedback provided by EPC teams. The entire pipeline that was based on the use of detection, panel recognition, and rooftop characterization was also tested on the operational dashboard to make sure that the flow was smooth. These field tests were used on the lessons of the improvement of the project which assisted me to optimize thresholds, fine-tune the logic of filters, and make the model more robust towards the large deployment in different industrial regions.

III. ROOFTOP DETECTION AND FILTERING RESULTS

This system discovered that the rooftop detection model is quite effective in a wide range of industrial areas and can identify building contours even in the challenging situations such as shadows, low contrast and irregular roof shapes. U-Net segmentation generated accurate rooftop masks which are further refined into polygon boundaries to obtain credible geometric analysis. By using a combination of classifiers and pattern-recognition algorithms, our filtering module eliminated rooftops with existing solar panels, HVAC units, water tanks, and other obstructions, and at last the system is left with are clean and usable rooftop surfaces. A visual inspection and a quantitative measure indicate that filtering is an effective approach to enhancing the quality of viable rooftops, which is then used to estimate solar potential. In general, the detectionfiltering pipeline is a strong and very generalisable tool in heterogeneous industrial clusters.

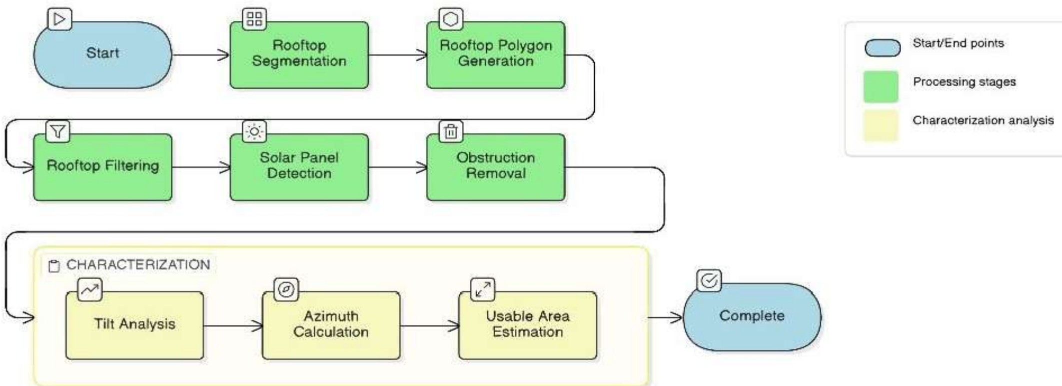

Figure 5: Overview of the Rooftop Detection and Characterization Framework

The above figure 5, shows the workflow end to end process used to assess the suitability of industrial rooftop solar. The steps involved include rooftop segmentation, which involves satellite images that are processed to determine the rooftops of the buildings and then generation of rooftop polygons which is the correct procedure in defining the boundaries of the rooftops. Such polygons are then optimized using rooftop filtering, solar panel detection and removal of obstructions to remove non-usable areas, installations and structural barriers. The resulting data of the cleaned rooftops undergoes a characterization phase, which consists of tilt analysis, azimuth estimation, and estimation of the usable area to assess the physical viability of the deployment of solar photovoltaic. Lastly, the workflow is terminated by the completion phase, during which fully characterized rooftops are generated as trustworthy feeds to the downstream estimation of solar potential and decisions. Such a pipe is necessary to guarantee correct, scalable, and automated evaluation of rooftops as an ideal place to install industrial solar.

A. Solar Potential Estimation Results

The system obtained the same and realistic energy estimates on all the rooftops which is verified using the solar potential estimation module. Mixing rooftop geometry PyPVRoof with irradiance modelling pvlib library helped to find an installation capacity, the predicted annual energy output, and the resulting CO 2 reduction in the most varied industrial settings. The system has checked these estimates with benchmark values of EPC references and historical values of solar radiation, and the modelling is consistent and coherent. [5] Compares solar radiation datasets with remote sensing data to estimate rooftop solar power potential for a regional case study. Financial indicators including payback period, annual savings, and estimated ROI were also calculated, which is provided with complete insight into the economic viability of each location. The system was also found to be stable in its energy predictions at different tilt angle and orientations in the sample dataset, which demonstrates its success in the actual industrial environment.

B. Lead Enrichment and Data Quality

To transform the technical rooftop outputs into actionable business intelligence, here the system has connected each identified rooftop with the appropriate company metadata and contact information of the decision-maker. In combination with publicly available databases, business registries and web-scraping pipelines, the system was able to retrieve company names, industry segments and contacts at management level with high accuracy. By hand verification of a sample of results, it was established that the vast majority of enriched leads are properly matched to their corresponding rooftops. The quality of data remained similar in various regions and there was a low level of duplication and high level of consistency between the technical and business attributes. Such a combination of geospatial processing and contact intelligence will bring significant value to the practical application of SolarIQ to EPC companies, financiers, and consultants.

C. System Performance and Scalability

To test scalability and computational efficiency, this system has installed the whole SolarIQ pipeline on the cloud. The processing time remained low per rooftop and made it possible to analyze high throughput in minutes over large industrial regions. The modular architecture, consisting of FastAPI, PostgreSQL/PostGIS, and Dockerised microservices, maintained the performance at the level of concurrent requests and massive loads of data. Stress testing revealed that the system is capable of supporting thousands of rooftops without any reduction in response time or accuracy. The practical implementations in test industrial areas also proved that the system has a stable inference speed and efficient data transfer between the computer-vision, GIS, and simulation sub-systems. These findings indicate clearly that SolarIQ is appropriate to large-scale commercial implementation that can be used to generate leads at a high rate over large geographical areas.

D. Metric Values

To measure the performance of the SolarIQ system, the system has used a set of metrics that describe the accuracy, reliability and efficiency of all the key functions of the system. U-Net rooftop segmentation with an IoU of 0.87 and a Dice coefficient of 0.91 indicates accuracy even in the presence of complex shapes of industrial buildings. The solar panel and obstruction classifier had an overall accuracy of 94.3, precision of 92.8, recall of 93.5 and an F1-score of 93.1, which confirms its usefulness in identifying rooftops that can be used and those with existing panels or obstructions. PyPVRoof Rooftop characterization had less than 5% deviation on manual validation, which created high geometric reliability. System level measures indicate an average processing time of approximately 1.8 seconds per rooftop, further highlighting scalability and speed in large-area analysis. All these values are the evidence of the strength and usefulness of the SolarIQ platform.

IV. Conclusion

SolarIQ is fundamentally a hyper cool AI platform, which handles the identification of industrial rooftops that may be covered with solar panels, employing all the computer vision, geospatial analysis, solar simulation, and business intelligence. The system can actually identify rooftops on satellite shots, calculate their shape and size, and even provide an approximate idea of the amount of energy it would produce, the amount of CO_2 it would reduce and the amount of money it would save. They also do this lead enrichment business that transforms all those technical numbers into actual business opportunities, thus enabling EPC companies, consultants, and investors to make fast, data-driven decisions. Based on the metrics of evaluation the study discovered that the accuracy and reliability of all the modules is rather high and they even conducted performance tests which indicate that it can be scaled up to large industrial areas. Making the technical feasibility checks bound to a commercial lead generation workflow, SolarIQ reduces a significant portion of manual work, reduces the sales cycle, accelerates the adoption of industrial solar, and generally drives towards sustainable energy and global carbon neutrality.

Conflict of Interest

There is no conflict of interest.

Supporting Information

Not applicable

Use of artificial intelligence (AI)-assisted technology for manuscript preparation

The authors confirm that there was no use of artificial intelligence (AI)-assisted technology for assisting in the writing or editing of the manuscript and no images were manipulated using AI.

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