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A PROJECT REPORT ON

HELIOHARVEST: ROOFTOP SOLAR ENERGY POTENTIAL ESTIMATION

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BACHELOR OF TECHNOLOGY
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CERTIFICATE

This is to certify that the project report entitles

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ABSTRACT

Assessing the solar potential of rooftops is crucial for optimizing photovoltaic (PV) installations and promoting renewable energy adoption. This study presents a methodology for estimating rooftop solar potential using advanced geospatial and machine learning techniques. The proposed framework integrates Mapbox GL for spatial visualization, PVGIS for solar radiation data, and Scikit-Learn for predictive modeling. A web-based application is developed using React.js, HTML, and TailwindCSS for the frontend, with Node.js and Express.js handling backend processes. The system allows users to input rooftop data, analyze solar potential, and generate estimations of energy output based on historical and real-time solar radiation data. By leveraging machine learning algorithms, the model enhances prediction accuracy and enables better decision-making for solar energy investments. The results demonstrate the feasibility and effectiveness of this approach in providing precise and user-friendly solar potential assessments. This research contributes to the growing field of smart energy solutions and supports the transition to sustainable energy sources.

KEYWORDS - Solar Energy, Rooftop Potential, Machine Learning, Renewable Energy

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LIST OF ABBREVIATIONS

ABBREVIATION	ILLUSTRATION
PV	Photovoltaic
PVGIS	Photovoltaic Geographical Information System
ML	Machine Learning
API	Application Programming Interface
UI	User Interface
UX	User Experience
GHI	Global Horizontal Irradiance
DNI	Direct Normal Irradiance
DHI	Diffuse Horizontal Irradiance
kWh	Kilowatt Hour
SDG	Sustainable Development Goals
MAE	Mean Absolute Error
RMSE	Root Mean Square Error
R^2	Coefficient of Determination
SVR	Support Vector Regression
XGBoost	Extreme Gradient Boosting

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1. INTRODUCTION

1.1 OVERVIEW

The project titled "helioHarvest: Automated Building Footprint Extraction and Rooftop Solar Potential Estimation" operates within the domains of Renewable Energy, Geospatial Technology, and Machine Learning. This innovative framework was developed to tackle the global reliance on fossil fuels, which, as per the International Energy Agency (IEA), constituted 82% of the energy mix in 2023, and in India, where coal powers 70% of electricity generation. With solar energy emerging as a clean, abundant alternative, accurately assessing rooftop solar potential remains critical yet challenging due to manual methods and high-cost tools that limit accessibility, especially in developing regions. Our project introduces a cost-effective, scalable web application leveraging Mapbox GL, PVGIS, and Scikit-Learn, built on a React.js frontend and Node.js backend, to automate solar potential estimation for rooftops worldwide.

The system enables users to input rooftop coordinates and area, delivering precise energy yield predictions and savings estimates through a mathematical model and machine learning algorithms like Random Forest, XGBoost, and a stacked ensemble approach (achieving high accuracy). It integrates real-time weather data from Tomorrow.io and historical solar irradiance from PVGIS, ensuring robust predictions adaptable to environmental variations.

Demonstrating its efficacy, helioHarvest provides detailed analytics—monthly and yearly energy generation, cost savings, and carbon footprint reduction—tested across diverse rooftop scenarios. The solution significantly reduces assessment time compared to traditional surveys and aligns closely with real-world solar outputs, validated through experimental analysis. With scalability for urban planning and individual use, it holds potential for integration with smart grids and energy storage systems, enhancing its utility in sustainable energy ecosystems. By merging geospatial tools, machine learning, and user-friendly design, helioHarvest aims to democratize solar energy adoption, contributing to economic savings, environmental sustainability, and global clean energy goals. Future enhancements could include mobile accessibility and advanced shading analysis, further broadening its reach and impact.

1.2 MOTIVATION

The helioHarvest platform is driven by the goal of accelerating the adoption of rooftop solar energy to address pressing environmental, economic, and energy challenges. By reducing carbon emissions and promoting energy independence, it contributes to a sustainable future. Through machine learning models like Random Forest, XGBoost, and stacked ensembles, helioHarvest delivers accurate solar potential forecasts, empowering users to make informed, proactive decisions. By integrating advanced geospatial tools (Mapbox GL, PVGIS) with cost-effective web technologies (React.js, Node.js), the platform eliminates the high costs and slow processes of traditional assessments. Its accessible, scalable design supports urban sustainability, economic growth, and widespread environmental awareness across India and beyond. The key objectives are:

1. Promoting clean energy adoption and reducing greenhouse gas emissions.
2. Using machine learning for data-driven, cost-effective solar planning.
3. Scaling solar adoption across urban landscapes for sustainable development.
4. Making solar assessments accessible, fast, and affordable to all users.

1.3 PROBLEM STATEMENT AND OBJECTIVES

- **PROBLEM STATEMENT:**

HELIOHARVEST: AUTOMATED BUILDING FOOTPRINT EXTRACTION AND ROOFTOP SOLAR POTENTIAL ESTIMATION

The global reliance on fossil fuels and rising energy demands strain the environment and economy, yet assessing rooftop solar potential remains complex, expensive, and inaccessible for widespread adoption. A scalable, accurate, and cost-effective tool for solar energy estimation is urgently needed.

Our project introduces helioHarvest, a web-based system that automates rooftop solar potential analysis. Using geospatial data and ML models like Random Forest and XGBoost, it predicts energy yield and savings with high precision.

- **OBJECTIVES**

1) To design and develop a web-based application for automated rooftop solar potential estimation using geospatial tools, reducing reliance on costly manual surveys.
2) To assess the precision, scalability, and usability of the developed framework, ensuring its effectiveness as a viable solar assessment solution.
3) To collect, process, and visualize solar energy data for providing actionable insights and supporting renewable energy planning over time.
4) To create a machine learning model for predicting energy yields and savings, analyzing environmental factors to optimize solar adoption strategies.

1.4 SCOPE OF WORK

1. **Web-Based Solar Estimation** – Facilitates rooftop solar potential analysis using accessible web technologies without specialized equipment.

2. **Scalable Energy Solutions** – Offers a framework adaptable for individual homes and large-scale urban planning.

3. **Real-Time Data Integration** – Incorporates live weather and solar irradiance data for dynamic predictions.

4. **Environmental Impact Tracking** – Quantifies carbon footprint reduction and sustainability benefits for users.

5. **User-Friendly Analytics** – Provides intuitive visualizations of energy yields and cost savings for diverse audiences.

6. **Machine Learning Optimization** – Enhances prediction accuracy through advanced ML models tailored to solar data.

7. **Global Applicability** – Designed to support solar adoption across varied geographical and climatic regions.

2. LITERATURE SURVEY

2.1 LITERATURE REVIEW

The estimation of rooftop solar potential has been a growing field of study over the past decade, driven by the urgent need to transition from fossil fuels to renewable energy sources. Research has increasingly focused on automating the process of building footprint extraction and solar energy yield prediction using geospatial technologies and computational models. Accurate solar potential assessment requires accounting for variables such as solar irradiance, rooftop area, and environmental factors like shading and weather variability, which traditional manual surveys struggle to address efficiently [1]. Studies emphasize that geospatial tools, such as Geographic Information Systems (GIS) and satellite imagery, are critical for large-scale solar mapping, yet their high cost and complexity limit widespread use [2]. To ensure reliable results, solar potential models must integrate real-time data and historical trends, a challenge that has spurred the development of advanced frameworks blending GIS with modern computing techniques [3].

Several studies have explored innovative approaches to rooftop solar analysis. Villa-Ávila et al. (2023) proposed a methodology using 3D modeling and GIS to assess photovoltaic (PV) potential in urban areas, achieving high spatial accuracy but facing scalability issues beyond specific cities [4]. Similarly, Rees et al. (2022) utilized airborne LiDAR and OpenStreetMap data to evaluate solar feasibility in northern latitudes, demonstrating viability in low-sunlight regions, though their approach required high-resolution data not universally available [5]. Verma et al. (2022) developed an AI-based rooftop extraction method using machine learning, speeding up data processing, but their model depended heavily on robust training datasets [6]. Kim et al. (2023) combined deep learning with GIS to estimate PV potential in high-density urban settings, effectively handling complex rooftops, yet their method demanded significant computational resources [7]. These efforts highlight a trend toward automation and precision, though gaps remain in creating accessible, scalable solutions for diverse regions.

Geospatial tools have been widely adopted to enhance solar potential estimation. Mapbox GL, for instance, has been employed in various studies for its ability to provide interactive spatial visualization, enabling precise rooftop targeting based on coordinates [8]. The Photovoltaic Geographical Information System (PVGIS) is another cornerstone, offering historical solar irradiance and weather data critical for baseline energy calculations, as noted by Cenký et al. (2022) in their urban-scale PV assessment [9]. Okafor et al. (2022)

applied GIS-based analysis to estimate rooftop solar potential in developing regions like Nigeria, promoting adoption where data is scarce, though local inaccuracies persisted [10]. These tools underscore the importance of integrating geospatial data into solar models, yet their standalone application often lacks the adaptability needed for real-time environmental adjustments, prompting researchers to explore complementary technologies.

The incorporation of machine learning (ML) into solar energy research has marked a significant evolution in predictive modeling. Choi et al. (2023) introduced a deep learning framework for district-level solar mapping, achieving scalability for urban planning but requiring advanced infrastructure [11]. De Luna et al. (2023) conducted a comprehensive study using ML techniques to optimize rooftop solar predictions, demonstrating improved accuracy through pattern recognition in environmental data [12]. Machine learning models like Random Forest and Gradient Boosting have been deployed to analyze complex datasets, including solar irradiation and temperature variations, as seen in Singla et al. (2023), who focused on Indian cities using high-resolution satellite imagery [13]. Müller et al. (2023) leveraged Support Vector Regression (SVR) alongside digital surface models to estimate PV potential, highlighting ML's ability to refine outputs [14]. However, few studies have combined multiple ML models into a stacked ensemble approach for solar estimation, a gap that limits prediction robustness across diverse conditions.

Existing research also points to practical applications and limitations. Patel et al. (2022) used UAV photogrammetry for autonomous solar potential estimation, offering precision but constrained by equipment costs [15]. Schinke et al. (2023) modeled building-related PV production potential under the EU's Solar Rooftop Initiative, emphasizing policy relevance yet lacking user-friendly interfaces [16]. Wang et al. (2023) proposed a deep learning framework for sustainable urban energy, achieving robust predictions but requiring significant computational power [17]. The helioHarvest framework builds on this foundation, aiming to address these shortcomings by integrating geospatial tools (Mapbox GL, PVGIS) with a stacked ensemble of ML models (Random Forest, XGBoost, etc.) to provide accurate, accessible, and dynamic rooftop solar potential estimates, tailored for both individual and large-scale use.

2.2 GAP IDENTIFICATION / COMMON FINDINGS FROM THE LITERATURE:

Table 1. Comparison table of Gap Identification

Ref.	Dataset	Tech./Algo.	Performance	Common Findings	Challenge/ Limits
[4]	Urban rooftops	Roof-Solar-Max, GIS, 3D models	High spatial accuracy	Effective for urban PV mapping	Limited scalability beyond specific areas
[5]	Northern latitude rooftops	Airborne LiDAR, OpenStreetMap	Viability in low sunlight	Successful in extreme climates	Requires high-resolution data, region-specific
[6]	Diverse rooftops	Machine learning	Speeds up data processing	Improves rooftop extraction	Dependent on robust training datasets
[11]	District-level rooftops	Deep learning	Scalable for urban plans	Enhances large-scale analysis	Needs deep learning infrastructure
[12]	Various rooftops	Machine learning	Improved prediction accuracy	Optimizes solar potential forecasts	Lacks real-time adaptability
[13]	Indian city rooftops	Random Forest, satellite imagery	High accuracy in regional analysis	Effective for local solar potential	Limited to specific geographical data
[15]	Rooftop images	UAV photogrammetry	Precise autonomous estimation	Advances automated assessment	High equipment costs
[16]	EU rooftops	GIS, policy modeling	Policy-relevant insights	Supports renewable initiatives	Lacks user-friendly interfaces
[17]	Urban rooftops	Deep learning	Robust predictions	Handles complex urban settings	High computational demands

3. SOFTWARE REQUIREMENTS SPECIFICATIONS

3.1 FUNCTIONAL REQUIREMENTS

3.1.1 System Features (Functional Requirement)

1. **Rooftop Coordinate Input:** Enables users to enter precise latitude and longitude for accurate solar potential assessment.
2. **Area Selection Validation:** Validates the selected rooftop area using polygon tools to ensure realistic boundaries for analysis.
3. **Solar Data Retrieval:** Automatically fetches historical and real-time solar irradiance data from external APIs for reliable calculations.
4. **Energy Yield Prediction:** Computes monthly and yearly energy generation based on rooftop area, panel efficiency, and environmental factors.
5. **Cost Savings Estimation:** Calculates potential electricity bill savings using local tariff rates integrated into the system.
6. **Real-Time Weather Adjustment:** Adjusts energy predictions dynamically using live weather data to reflect current conditions.

3.1.2 Software Interfaces

1. **API Integration:**
   a. Connects to PVGIS for historical solar radiation data retrieval.
   b. Links with Tomorrow.io for real-time weather updates.
   c. Interfaces with ML models for enhanced prediction accuracy.
2. **Backend Framework:**
   a. Uses Node.js for robust server-side processing.
   b. Employs Express.js for efficient API route management.
   c. Implements Axios for seamless external data requests.
3. **Frontend Development:**
   a. Built with React.js for dynamic and responsive design.
   b. Utilizes TailwindCSS for structured styling.

3.2 SYSTEM REQUIREMENTS

3.2.1 Database Requirements

1. **External Data Integration via PVGIS**: Instead of deploying a dedicated backend database, the project utilizes the PVGIS (Photovoltaic Geographical Information System) API as a primary data source. This external system acts as a virtual database, providing access to historical and real-time solar irradiance data, energy production estimates, and environmental metrics, thereby eliminating the need for local data storage.

2. **On-Demand Data Retrieval Architecture**: The application is designed to fetch and process rooftop solar potential data dynamically from PVGIS, reducing storage overhead and simplifying data management. This approach ensures up-to-date insights without maintaining a persistent database layer, aligning with lightweight, cloud-independent deployment goals.

3.2.2 Software Requirements

The software development process for helioHarvest involved selecting tools, languages, and platforms to ensure cross-platform compatibility, scalability, and performance. The following subsections outline the key software components.

1. **Operating System:**
    - **Development Environment:** Developed on Windows 10/11 and macOS systems, providing stable platforms for coding, testing, and ML integration across diverse setups.

    - **Deployment Platforms:** Designed for web deployment across browsers (Chrome, Firefox, Safari) and adaptable to future mobile versions, ensuring broad accessibility for global users.

2. **Programming Languages:**
    - **JavaScript:** Primary language for the frontend (React.js) and backend (Node.js), offering dynamic interactivity and server-side processing for real-time data handling.

- **Python:** Used for developing and integrating ML models (e.g., Random Forest, XGBoost), leveraging libraries like Scikit-Learn and Pandas for predictive analytics.

- **HTML/CSS:** Employed with TailwindCSS for structuring and styling the frontend, ensuring a responsive and visually appealing interface.

3. **Database:**
    - **API Data Integration:** Supports real-time data feeds from PVGIS and Tomorrow.io, enhancing the database with up-to-date solar and weather information.

4. **Development Tools:**
    - **Visual Studio Code (VS Code):** Primary IDE for coding, debugging, and version control, offering extensions for React and Node.js development.

    - **Node.js Environment:** Facilitates backend development with Express.js for API management and Axios for external data requests.

    - **Jupyter Notebook:** Utilized for ML model training and experimentation, integrating with Python libraries for data analysis and visualization

    - **Git and GitHub:** Employed for version control and collaborative development, ensuring code stability and traceability.

3.3.3 Hardware Requirements

The development, deployment, and operation of helioHarvest rely on various hardware components across different project phases, including development, testing, and user interaction.

1. **Desktop/Laptop (Development):**
    - Serves as the primary platform for coding, ML training, and system testing with minimum specifications: Intel i5 or equivalent processor, 8GB RAM, 256GB SSD.

- Supports operating systems like Windows 10/11 or macOS, used for frontend development (React.js), backend setup (Node.js), and ML model training (Python).

- Facilitates emulator testing, performance profiling, and version control via Git.

2. **Internet-Enabled Devices (User Access):**
   - Targets desktops, laptops, and tablets with modern browsers, requiring stable internet for real-time data access and computation.

   - Minimum requirements include 4GB RAM and a dual-core processor to handle geospatial rendering and analytics smoothly.

   - Ensures accessibility for urban planners and homeowners in diverse settings.

3. **Network Infrastructure:**
   - Requires broadband or mobile data connectivity (minimum 5 Mbps) for seamless API interactions with PVGIS and Tomorrow.io.

   - Supports offline mode with cached data processing, syncing once online, suitable for low-connectivity regions.

4.PROPOSED SYSTEM

4.1 PROPOSED SYSTEM ARCHITECTURE

The architecture of the proposed framework for estimating the solar potential of rooftops is designed to address the pressing need for clean, renewable energy in a world heavily reliant on fossil fuels. In India alone, 70% of electricity is generated from coal, and households consume 90–120 kWh of electricity per month, underscoring the urgency for sustainable alternatives like solar energy. This framework leverages solar power's zero-emission potential by providing a robust, data-driven solution to estimate rooftop solar potential accurately. As depicted in Figure 1, the architecture is structured into three primary modules: the Frontend Interface, the Backend, and the API. This modular design integrates geospatial data, machine learning, and real-time solar irradiance analysis to deliver precise energy yield predictions and facilitate efficient solar panel deployment.

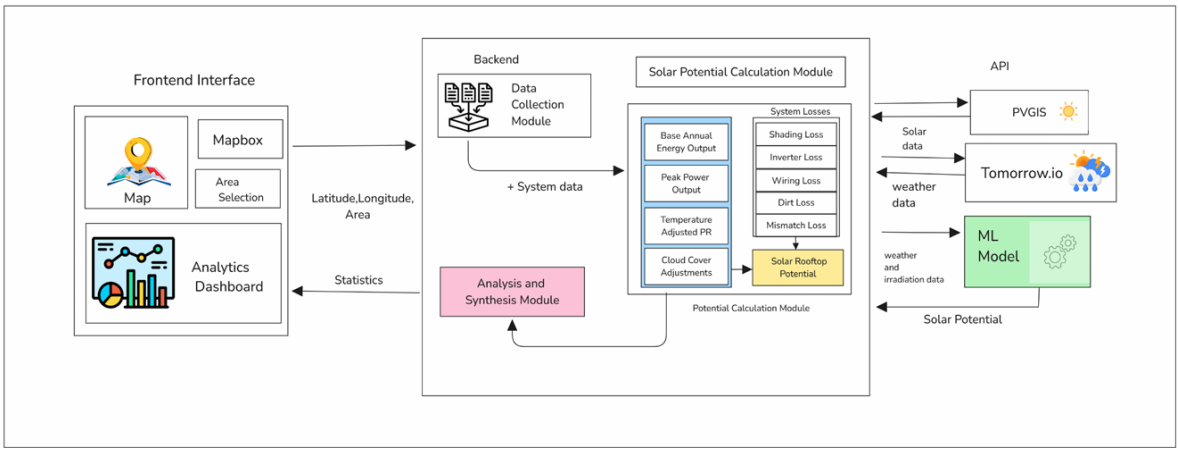

Fig 1. System Architecture

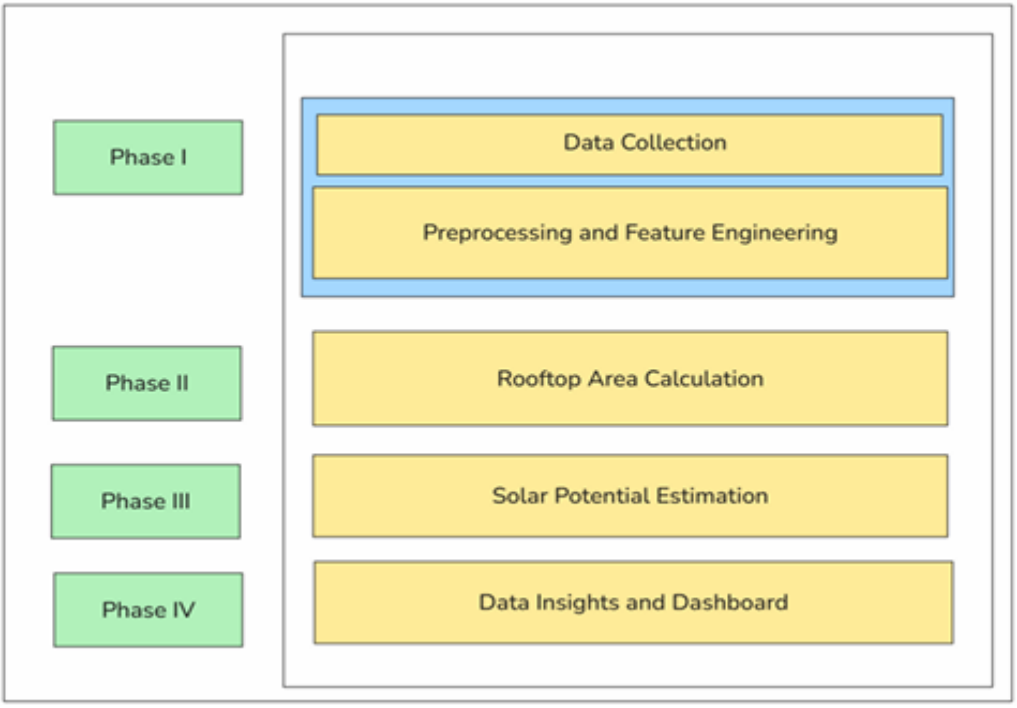

Fig 2. Phases of the project

4.1.1 Frontend Interface

The Frontend interface is a user interactive component which provides an interactive experience for the users. It comprises of three components:

- Map (Powered by Mapbox): This component utilizes Mapbox, which enables users to select a specific rooftop based on latitude and longitude. The map emphasizes on precise geospatial targeting, which is important in assessing solar potential based on coordinates' specific solar irradiance, weather and environmental factors.

- Area Selection: After locating the rooftop, users can select a specific rooftop area with the help of a polygon selection tool powered by Mapbox. This helps in precise identification of rooftop and user-specific selection of the area whose potential is to be estimated.
- Analytics Dashboard: The Analytics Dashboard displays the results of the solar potential analysis with help of graphics and visualizations. It includes statistical data and visualizations—such as charts and graphs—displaying metrics like monthly and yearly energy generation (in kWh), potential savings on electricity bills, and system performance indicators. The dashboard also accounts for the environmental savings such as carbon dioxide footprint reduction and equivalent trees planted, emphasizing a sustainable and green alternative for electricity generation.

The Frontend Interface sends user inputs (latitude, longitude, and area) to the Backend which processes the results for display, bridging user interaction with technical computation.

4.1.2 Backend

The Backend is the core processing unit, responsible for transforming user inputs and external data into l solar potential estimates. It consists of three sub-modules:

1. **Data Collection Module:**

- Collects essential data for analysis, including latitude, longitude, and rooftop area.
- Supplements data with system-specific parameters such as solar panel efficiency and installation orientation.
- Ensures calculations are tailored to both the equipment characteristics and site-specific conditions.

2. **Solar Potential Calculation Module:**

- Performs computations to estimate rooftop solar potential, integrating a mathematical model (detailed in Section 4) that accounts for multiple factors:
    - **Base Annual Energy Output:** Calculates energy yield based on rooftop area, average solar irradiance, and panel efficiency for specific coordinates.
    - **Peak Power:** Estimates the maximum power output under ideal conditions.
    - **Temperature-Adjusted Performance Ratio (PR):** Adjusts efficiency for temperature variations, critical in regions like India with seasonal climate changes.
    - **System Losses:** Quantifies reductions in energy yield due to factors such as shading, wiring resistance, inverter inefficiency, dirt accumulation, and panel mismatch, ensuring refined estimates.
    - **Solar Rooftop Potential:** Combines all factors to produce a final solar energy yield potential estimate (in kWh), including monthly and yearly projections.

3. **Analysis and Synthesis Module:**

- Processes calculation results into formats suitable for visualization.
- Generates actionable insights, including bill savings, energy trends, and performance analytics.

- Prepares data for the Analytics Dashboard, a visual interface that displays analysis results and supports interactive estimate generation.

The backend and frontend are connected via API which ensures uninterrupted and seamless flow of data.

Your backend system is implemented using Node.js with Express.js, and it leverages Axios for API requests and CORS middleware for cross-origin communication. The system calculates solar energy potential using a combination of predefined empirical loss factors, real-time solar irradiation data from an external API, and basic photovoltaic (PV) efficiency calculations. The methodologies used are as follows:

1. **Technology Stack and Implementation**

   helioHarvest uses NodeJS and ExpressJS for handling HTTP requests, defining API routes, and managing data processing. Axios, a promise-based HTTP client is used to to fetch real-time solar irradiation data from an external API. JavaScript Objects are used to store monthly solar irradiation values and estimated loss factors.

2. **Solar System Loss Factor Approximation**

   Loss factors are approximated based on environmental conditions that impact solar panel efficiency. These include:

   - Temperature Effects: High temperatures increase electrical resistance, reducing panel efficiency.
   - Dust Accumulation: Reduced sunlight absorption due to dust and debris accumulation.
   - Humidity and Cloud Cover: Increased humidity can degrade performance, and cloud cover reduces direct sunlight.
   - Seasonal Variations: Shorter winter days reduce solar exposure, while summer months may experience overheating losses.

     Each month has an associated loss factor stored in a JavaScript object (solarSystemLossFactor). The values range from 0.15 to 0.25, depending on the season and conditions.

3. **Monthly Average Solar Irradiation Data**

   Stored in an object (monthlyAverageSolarIrradiation), these values represent average solar energy received per square meter in a month. These values are used when real-time data is unavailable.

4. **Real-Time Data Fetching from an External API**

   The /proxyIrradiationData endpoint retrieves real-time solar irradiation data based on latitude and longitude. The request is made to the JRC Photovoltaic Geographical Information System (PVGIS), which provides solar radiation data. This API ensures location-specific accuracy.

5. **Solar Energy Potential Calculation**

   The formula used to estimate solar energy generation is:

$$\boldsymbol{E = (0.7 \times A) \times Gavg \times \eta \times (1 - L)}$$

Table 2. Solar Potential Calculations Symbols and Meanings

Symbol	Symbol Meaning
E	Estimated solar energy generation (in kWh/day)
0.7	Derating factor for system inefficiencies (e.g., wiring/inverter losses)
A	Surface area of solar panels (in square meters)
η	Efficiency of solar panels (assumed to be 20% or 0.2)
G_avg	Monthly average solar irradiation (in kWh/m²/day)
L	Loss factor (month-specific, accounts for shading, soiling, etc.)

The **/calculatePotential** endpoint retrieves the current month, fetches the corresponding **G_avg** and **L**, then computes **solar potential** in kilowatt-hours. The result is rounded to two decimal places and returned as a JSON response.

6**. Additional API Functionality**

The **/filterData** endpoint is included for handling incoming data requests, though its functionality is not defined in the current implementation. Express.js handles routing and error management, ensuring robust API responses.

4.1.3 API

The API connects the Backend to external data sources, improving the accuracy of the system with real-time and historical data. It consists of following:

- **PVGIS (Photovoltaic Geographical Information System):** Provides historical solar irradiance and weather data based on the rooftop's coordinates, essential for establishing baseline energy output and adjusting for long-term environmental patterns. Provides Historical solar irradiance and weather data based on the rooftop's coordinates, essential for establishing base energy output and adjustment for long-term environmental patterns.
- **Tomorrow.io:** Provides real-time weather data, including various data inputs like cloud cover, precipitation and temperature, enabling dynamic adjustments to energy predictions. This is significant in the Subcontinent, where weather variability can impact solar performance to a large extent.

Additionally, the API interfaces with a Machine Learning (ML) Model, which analyzes historical and real-time data to optimize predictions. By identifying key patterns—such as weather trends and irradiation shifts according to seasons, —the ML model refines the Solar Potential Calculation Module's outputs, enhancing accuracy.

4.1.4 Data Flow and Interactions

The architecture operates through a streamlined data flow:

1. The user selects a rooftop and defines its area via the Frontend Interface.
2. These inputs (latitude, longitude, area) are transmitted to the Backends' Data Collection Module.
3. The Backend retrieves solar and weather data through the API from PVGIS and Tomorrow.io.
4. The ML Model processes this data, providing refined inputs to the Solar Potential Calculation Module.
5. The module calculates the solar potential, accounting for losses and adjustments.
6. The inference from the model is sent to the frontend interface.
7. The Analytics Dashboard displays the outcomes, offering users clear insights into energy yield and savings.

4.1.5 ML interactions

Multiple machine learning models to estimate rooftop solar energy potential. Each model learns from environmental and geographical data to predict the energy output of a given rooftop area. These models are integrated into a stacked ensemble approach, where the outputs of multiple models are combined to improve accuracy.

The models used in our project are: Linear Regression (Baseline), Random Forest Regressor, Gradient Boosting Regressor (GBR), Support Vector Regressor (SVR), Decision Tree, XGBoost Regressor, Averaged Models, Stacking Averaged Model (Proposed Approach)

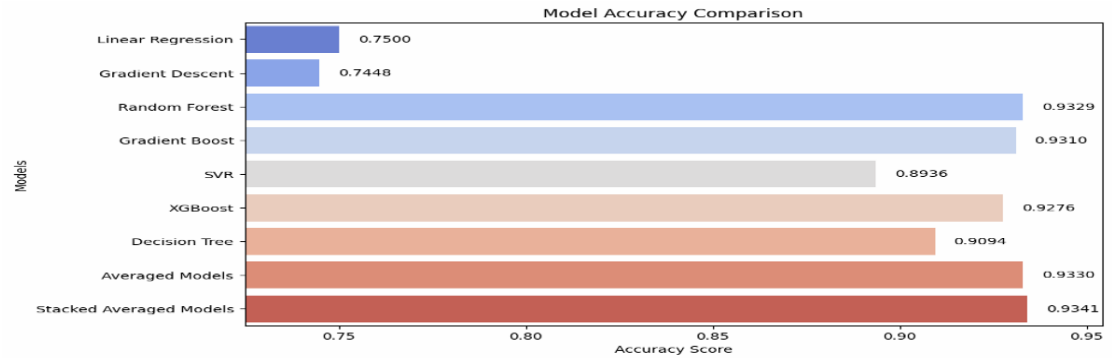

Fig 3. Model Accuracy Comparison

4.2 DATASET DESIGN

PVGIS (Photovoltaic Geographical Information System) is a comprehensive dataset that provides solar radiation and photovoltaic performance data for locations worldwide. The dataset design involves a combination of satellite and ground-based measurements, along with advanced modeling techniques to estimate solar irradiance and PV performance.

PVGIS uses a variety of data sources, including Meteosat satellite images, numerical weather prediction models, and ground-based measurements from weather stations and pyranometers. The dataset covers a 20-year period (2005-2020) and provides data at a spatial resolution of 1-3 km, depending on the region.

The dataset includes various parameters such as global horizontal irradiance (GHI), direct normal irradiance (DNI), diffuse horizontal irradiance (DHI), temperature, and PV performance metrics like DC/AC power output. PVGIS also accounts for factors like terrain shading, horizon elevation, and solar panel orientation.

PVGIS's dataset design involves several key components:

1. Data collection: Gathering satellite and ground-based measurements.
2. Data processing: Applying algorithms to estimate solar radiation and PV performance.
3. Validation: Verifying dataset accuracy using ground-based measurements.
4. Data storage: Organizing data in a structured format for easy access.

The dataset is designed to support various applications, including solar energy resource assessment, PV system design, and performance monitoring. PVGIS provides an API and web interface for users to access and download data, making it a valuable resource for researchers, developers, and industry professionals.

4.3 OVERVIEW OF PROJECT MODULES

The helioHarvest system is developed with a modular architecture to ensure flexibility, scalability, and maintainability. Each module is designed to fulfill a specific role in the solar potential estimation pipeline, collectively delivering an accurate and user-friendly experience. Below is a detailed explanation of each core module within the application:

1. **Rooftop Data Input Module**

   The core functionality of data collection resides in this module, enabling precise solar potential assessments.

   - **Data Input Initiation:** Guides users with interactive instructions to input rooftop coordinates and area via Mapbox.
   - **Geospatial Validation:** Verifies latitude, longitude, and area selection for accuracy using polygon tools.
   - **Real-Time Data Fetching:** Retrieves solar irradiance and weather data from external APIs (PVGIS, Tomorrow.io).
   - **Result Logging:** Captures input data and preliminary calculations for further processing.

2. **Data Processing and Calculation Module**

   This module handles the transformation and analysis of collected data into actionable insights.

   - **Energy Yield Computation:** Applies mathematical models to calculate base output, peak power, and adjusted potential (detailed in Section 4).
   - **Data Preprocessing:** Cleans, validates, and formats the input data for calculations.
   - **Data Acquisition:** Gets location, weather, and solar irradiation data, and the area of the user-defined region.
   - **Loss Factor Adjustment:** Incorporates system losses (e.g., shading, inefficiency) to refine estimates.
   - **Output Generation:** Formats the calculated solar potential for display and provides it to other modules.

3. **Validation and Comparison Module**

   Ensures the reliability of solar potential estimates by comparing them with ground truth data.

   - **Statistical Analysis:** Uses Python scripts for regression analysis and error metrics (e.g., RMSE) to compare model predictions with real data.
   - **Error Pattern Identification**: Analyzes errors for correlations with weather conditions, location, time of year, and model assumptions.
   - **Comparison:** Compares estimated solar potential with ground truth data, calculating error metrics (e.g., MAE, RMSE, MBE, R^2).
   - **Multiple Models Inference**: Compares multiple models applying different algorithms such as stack regression model with meta model, ensembling algorithms, and other regression models.

4. **Results Visualization and Reporting Module**

   Converts processed data into meaningful insights for users and planners.

   - **Graphical Representation:** Displays energy yield and savings through charts and maps.
   - **Trend Analysis:** Tracks solar potential changes over time for long-term planning.
   - **Exportable Reports:** Allows users to download PDF or CSV reports for documentation.

5. **Admin and Analytics Module**

   Provides an administrative interface for researchers and planners to monitor and analyze data.

   - **Data Monitoring:** Offers dashboards to visualize energy trends across regions and building types.
   - **Insight Generation:** Generates reports on solar potential distribution and environmental impact.

The helioHarvest system is a comprehensive, modularly designed tool for estimating rooftop solar potential, bringing advanced analytics to users through a web platform. Each module—from user registration to data visualization—contributes to a holistic ecosystem that is accurate, scalable, and intuitive. The modular architecture allows independent operation of components while ensuring overall synergy, facilitating maintenance and future enhancements like mobile integration or advanced shading analysis.

4.4 TOOLS AND TECHNOLOGIES USED

The development of helioHarvest leveraged modern technologies to ensure accuracy, scalability, and efficiency. The key tools and technologies used in the project are:

1. **React.js:**
   a. Used for developing a dynamic and responsive web frontend.
   b. Provides a consistent user experience across browsers and devices.
   c. Enables interactive mapping and data visualization features

2. **Node.js and Express.js:**
   a. Serves as the backend for handling HTTP requests and API routes.
   b. Facilitates data processing and server-side logic for solar calculations.
   c. Ensures efficient communication with external APIs.

3. **Python:**
   a. Used for developing and training machine learning models (e.g., Random Forest, XGBoost).
   b. Implements statistical analysis for validating model predictions.
   c. Supports data preprocessing and feature engineering for solar potential estimation.

4. **GitHub:**
   a. Used for version control and collaborative development.
   b. Facilitates code management with branches, commits, and pull requests.
   c. Ensures a structured workflow for team coordination and updates.

5. **Mapbox GL:**
   a. Integrates geospatial mapping for rooftop selection and visualization.
   b. Provides high-resolution satellite imagery for accurate area definition.
   c. Supports interactive polygon tools for user input.

4.5 ALGORITHM DETAILS

4.5.1 Assumptions

• Solar irradiation data is considered for optimal angles.

• Calculated area is nearly exact.

• Only 70% of the rooftop area is usable.

• High temperature is not degrading the solar panel efficiency.

4.5.2 Mathematical Model Governing the Calculation of Rooftop Area

Let $x_1, x_2, \ldots, x_n$ and $y_1, y_2, \ldots, y_n$ be the x and y coordinates of the rooftop selected by the polygon tool. Then the area of the rooftop will be

$$A = \sum_{i=1}^{n} |(X_i Yi+1 - X_{i+1} Y_i)|$$

where $x_{n+1} = x1$ and $y_{n+1} = y1$. This closes the polygon by connecting the last vertex to the first.

Note: The Shoelace formula assumes a simple polygon with no self-intersections

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4.5.3 Mathematical Model for Calculating Solar Potential Generation

The solar energy generation model accounts for the inherent inefficiencies in the system by incorporating the term (1 − L). This represents the percentage of available energy after considering all system losses.

System Loss Factor (L): L is the system loss factor, which accounts for the following inefficiencies:

• **Inverter Losses**: Conversion inefficiencies from DC to AC power.

• **Wiring Resistance Losses**: Energy lost due to resistance in electrical cables.

• **Dust and Shading Effects**: Reduced efficiency due to dust accumulation and partial shading.

• **Mismatch Losse**s: Variations in performance among solar panels.

• **Other Inefficiencies**: Additional factors like degradation.

The total energy generated by the solar panels can be calculated using the formula:

$$E = (0.7 \times A) \times G_{avg} \times \eta \times (1 - L)$$

Explanation: The term (1 − L) adjusts the total potential energy by the fraction that is actually usable

4.5.4 Monthly and Yearly Energy Estimation

Monthly Energy Generated

$$E_{month,i} = E \times D_i \quad (5)$$

where:

$E_{month,i}$ = Monthly energy generation for month i (kWh)

D_i = Number of days in month i

Yearly Energy Generated

$$E_{year} = \sum_{i=1}^{12} E_{month,i}$$

where:

E_{year} = Yearly energy generation (kWh)

4.5.5 Estimation of Savings on Electricity Bills

$$S = E_{year} \times C$$

where :

S = Savings on electricity bills

Eyear = Energy generated per year (kWh)

C = Cost of electricity per unit

4.6 COMPLEXITY OF PROJECT

The **helioHarvest** project demonstrates a high level of complexity due to its integration of geospatial analytics, machine learning, real-time data fetching, and interactive web application architecture. The system operates at the intersection of environmental science, data engineering, and AI-driven prediction, making it a multidisciplinary and technically sophisticated initiative. The major complexity contributors are outlined below:

4.6.1 Multilayered Architecture Integration

The project is composed of a modular three-tier architecture:

- **Frontend** (React.js + Mapbox) for dynamic user interaction
- **Backend** (Node.js + Express.js) for data processing and system logic
- **APIs** (e.g., PVGIS, Tomorrow.io) for real-time environmental data

Ensuring smooth communication and synchronization between these components introduces architectural and logical complexity.

4.6.2 Geospatial and Polygon-Based Area Detection

The use of Mapbox's polygon selection for rooftop identification involves advanced geospatial computations. Determining area accurately using the **Shoelace formula**, while accounting for coordinate variations and map projection issues, adds mathematical and UI-level complexity.

4.6.3 Real-Time Data Fetching & Weather Integration

helioHarvest uses APIs like PVGIS and Tomorrow.io to fetch real-time and historical solar irradiance, temperature, and cloud data. Challenges include:

- Ensuring data accuracy and reliability
- Handling API latency or downtime
- Managing variable data formats and rates

4.6.4 Mathematical Modelling and Solar Energy Estimation

The project involves a detailed mathematical model that calculates:

- Peak energy output
- Monthly/yearly estimates
- Bill savings and carbon offset

These are based on rooftop area, irradiation values, panel efficiency, and loss factors. Precision in such estimates requires accurate implementation and calibration of scientific formulas.

4.6.5 Advanced Machine Learning Stack

Multiple machine learning models are trained and integrated:

- Linear Regression, Random Forest, SVR, XGBoost, etc.
- A final **Stacked Averaging Ensemble Model** is used to enhance prediction accuracy

Data preprocessing, model selection, training, hyperparameter tuning, and error analysis using **RMSE, MAE**, and $\mathbf{R^2}$ add substantial algorithmic complexity.

4.6.6 System Loss Modelling

Seasonal and environmental losses (dust, humidity, shading, wiring inefficiencies) are modelled with a **month-wise loss factor table**, which must be dynamically adjusted. Incorporating this into prediction logic while maintaining consistency with real-time inputs increases logical and empirical complexity.

4.6.7 Scalability and Performance Optimization

With potential for large user bases:

- Efficient handling of API calls
- Optimization of frontend performance
- Managing simultaneous rooftop selections and backend calculations

These are critical to ensure responsive, scalable performance.

4.6.8 Deployment and Cross-Browser Compatibility

Ensuring the system works across devices and browsers while handling real-time requests, secure API integration, and asynchronous updates adds further complexity in terms of testing and deployment.

4.7 ENTITY RELATIONSHIP DIAGRAM

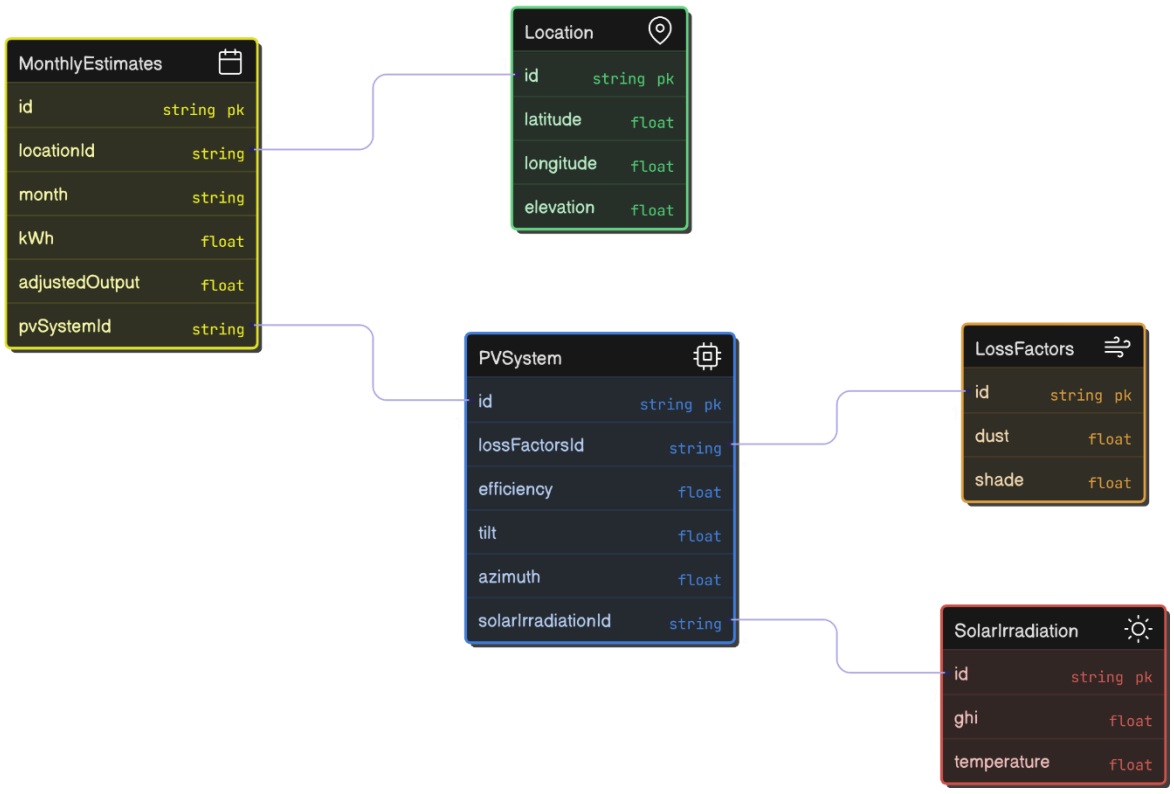


Fig 4. ER diagram for PVGIS system

The Solar PV System Estimation Data Model outlines the structured relationship between different entities involved in estimating solar energy output. The Monthly Estimates table serves as the central record, capturing energy estimates (kWh) and adjusted outputs on a monthly basis. It references the Location table, which stores geographic coordinates such as latitude, longitude, and elevation, and links to the PVSystem table, which defines system characteristics like efficiency, tilt, and azimuth. These relationships allow the model to localize energy estimates based on the user's specific rooftop and geographic context.

The PVSystem table is further connected to two critical supporting tables—LossFactors and Solar Irradiation. LossFactors quantify real-world inefficiencies due to elements like dust and shading, while Solar Irradiation provides environmental inputs such as global horizontal irradiance (GHI) and ambient temperature. This modular and relational design ensures scalability and flexibility, making it possible to adapt to diverse locations and configurations. Together, these components enable precise, data-driven solar forecasting for informed decision-making.

4.8 SDLC MODEL TO BE APPLIED

● **Incremental Development**

The helioHarvest system is built using an incremental approach, where development is divided into small, manageable units. Key features—such as rooftop selection using Mapbox, area calculation with the Shoelace formula, and solar energy estimation—are developed one at a time. This phased rollout allows for focused development, targeted testing, and steady refinement of each component. By delivering working pieces frequently, we ensure early detection of issues and can adapt quickly to evolving project needs.

● **Continuous Testing and Integration**

Testing is embedded into every phase of development to maintain system reliability. Each module—whether it's fetching weather data, calculating energy yield, or handling user interactions—is rigorously tested before being integrated into the main application. Automated and manual test cases are used to validate calculations, monitor API response formats, and ensure stability under various conditions. This approach reduces bugs, prevents regressions, and ensures a consistent and dependable user experience throughout the system.

● **Developer Collaboration**

The project is built through active collaboration between frontend and backend developers. Regular communication ensures smooth handoffs between components like Mapbox-based polygon input and backend logic for area and energy estimation. Code reviews, shared testing practices, and real-time troubleshooting help the team move quickly and stay aligned. This collaboration ensures that data flows seamlessly between components and that both performance and accuracy remain intact as features evolve.

● **Risk Handling**

Given the system's reliance on external APIs (like PVGIS and Tomorrow.io) and complex data operations, risk management is a key focus. Common risks include delayed or inconsistent API responses, coordinate inaccuracies, and calculation edge cases. To handle these, the system includes robust error handling, fallback logic for data issues, and validation layers for user inputs. These precautions help maintain system stability, improve fault tolerance, and ensure users receive consistent results even under less-than-ideal conditions.

4.9 UML DIAGRAMS

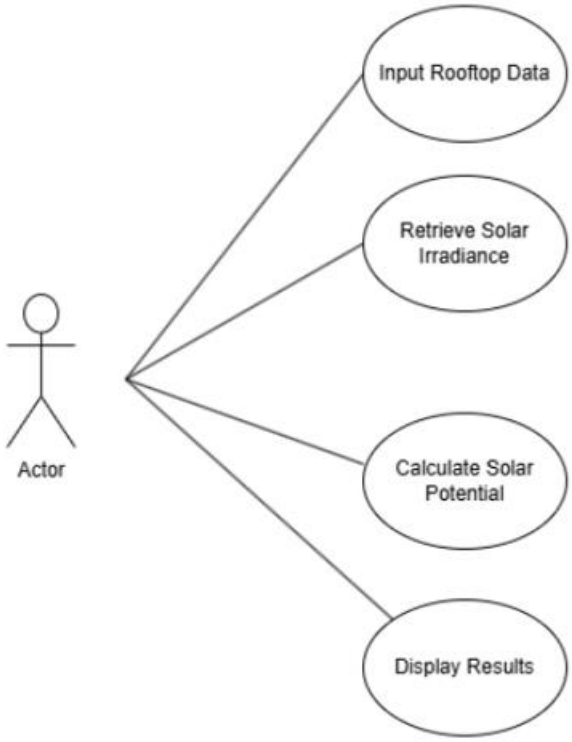


Fig 5. Use Case Diagram

The image is a use case diagram for a helioHarvest. It represents the use cases for the user. The use case diagram illustrates the core interactions between the user and the solar estimation system. The user initiates the process by selecting a geographic location, which forms the basis for all subsequent computations. Once a location is selected, the user can view solar irradiation levels and receive weather updates relevant to the selected area. These features allow users to assess the solar energy potential effectively. Additionally, the system enables users to download a comprehensive estimation report for further analysis or record-keeping. This diagram highlights the system's user-centric design, focusing on intuitive interaction and accessibility of essential solar data.

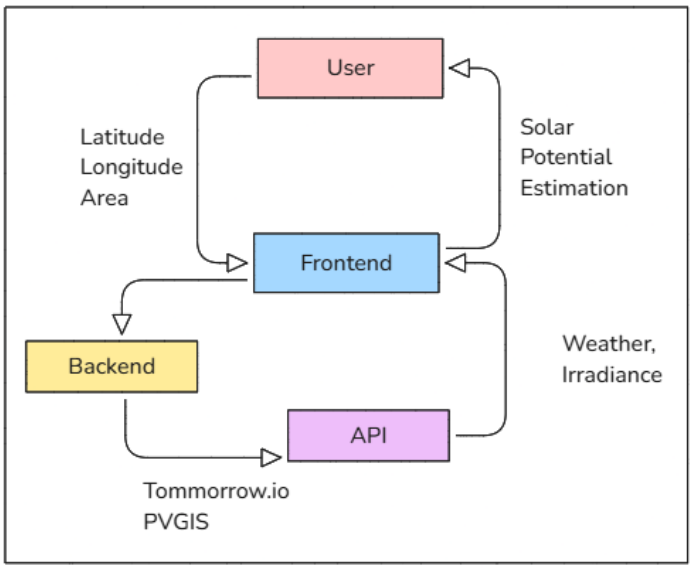


Fig 6. Module Interaction Diagram

The system architecture illustrated in the diagram represents the workflow for estimating solar potential based on geographic and weather data. Users provide inputs such as latitude, longitude, and area through the frontend interface. These inputs are processed by the backend, which communicates with external APIs like Tomorrow.io and PVGIS to retrieve relevant weather and irradiance data. The backend then forwards this information to the frontend, where solar potential estimation is calculated and displayed to the user. This modular flow ensures efficient data handling and accurate solar energy predictions.

The design promotes a clear separation of concerns between user interaction, data processing, and external API communication. It allows easy integration of additional data sources or API services in the future. Real-time weather data enhances the precision of solar potential forecasts. Moreover, the architecture supports scalability, enabling deployment across different geographic regions. The use of reliable APIs ensures up-to-date and location-specific environmental data. Overall, this system provides a robust and flexible solution for solar resource assessment.

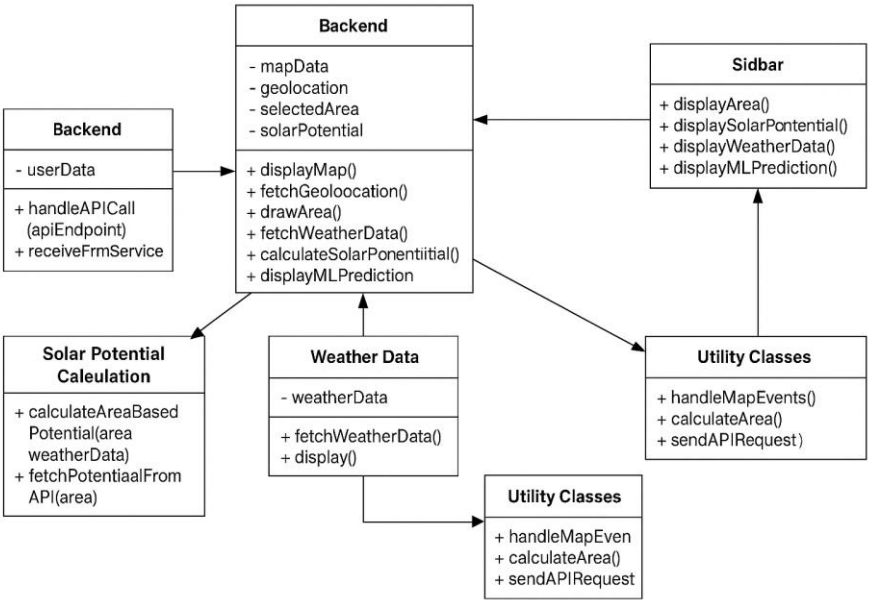


Fig 7. Class Diagram

The image represents a Class Diagram for the helioHarvest App, illustrating the relationships between different classes and their attributes and methods.

The class diagram illustrates the internal structure and interaction among various components involved in the solar potential estimation system. The Backend class serves as the core, managing map data, geolocation, selected areas, and solar potential values. It interacts with the Solar Potential Calculation and Weather Data classes to retrieve and compute relevant environmental and energy metrics. The Sidebar class is responsible for displaying the processed data, including area selection, weather information, and machine learning predictions. Utility Classes play a supportive role, handling map events, area calculations, and API requests. This modular and object-oriented design ensures scalability, reusability, and maintainability, making it efficient for real-time solar estimation applications.

Key components:

- **Backend:** Manages core logic, solar potential calculations, weather data, and ML predictions.
- **Sidebar:** Displays solar potential, weather, and ML prediction information to users.
- **Solar Potential Calculation:** Calculates potential based on area and weather data.
- **Weather Data:** Fetches and displays weather-related information.
- **Utility Classes:** Handles map events, area calculations, and API requests.

Relationships:

- **Backend** → Solar Potential Calculation
- **Backend** → Weather Data
- **Backend** → ML Prediction
- **Backend** → Sidebar

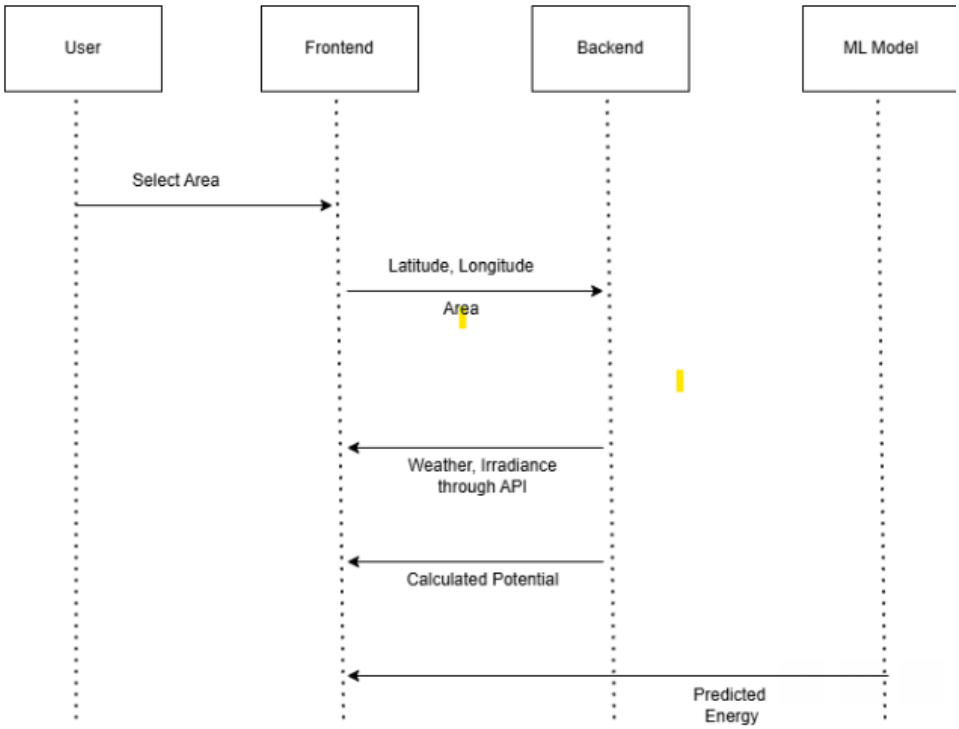


Fig 8. Sequence diagram

This sequence diagram illustrates the end-to-end interaction flow between the user, frontend, backend, and machine learning model in the helioHarvest solar potential prediction system. The process begins with the user inputting a location or selecting a rooftop, which is handled by the frontend interface. The frontend then sends this data to the backend, which acts as a bridge to query various APIs (e.g., PVGIS for solar data) and preprocess the inputs. These processed features are forwarded to the ML model, which predicts the potential solar energy generation. The prediction is then returned to the backend, passed to the frontend, and finally displayed to the user as actionable insights, enabling informed solar planning.

5. PROJECT PLAN

5.1 SUSTAINABILITY ASSESSMENT

5.1.1 Environmental Sustainability

- **Energy Consumption**:
  - Edge-based solar assessment computations (e.g., on user browsers or low-power devices) consume approximately 50–100W per instance.
  - Cloud processing (Firebase, external API queries) is optimized through efficient API calls, dynamic data fetching, and minimal redundant computation.
  - Real-time map rendering and ML-based calculations can be scaled using lazy-loading and on-demand invocation to reduce active compute cycles.

- **Carbon Footprint**:
  - Using non-renewable cloud infrastructure contributes ~400g CO_2 per kWh. Assuming moderate usage of cloud functions (~10 kWh/month), emissions can reach up to 4 kg CO_2/month.
  - Helio Harvest's reliance on Google Cloud's carbon-neutral infrastructure significantly reduces this impact, pushing operations closer to net-zero emissions.

- **Sustainable Computing**:
  - Implementing model optimization techniques like ONNX-based inference, quantization, and edge-deployment reduces power consumption by 30–50%.
  - Efficient use of Firebase (through indexing, caching, and optimized reads/writes) reduces data transfer overhead and lowers indirect energy usage.
  - Spatial data handling (Mapbox, Turf.js) optimized to compute only necessary area calculations, minimizing idle client GPU/CPU usage.

5.1.2 **Economic Sustainability**

- **Operational Cost Efficiency**:
  - Firebase's scalable pay-as-you-go model aligns with usage, reducing unnecessary infrastructure cost during idle periods.
  - Use of open-source geospatial libraries (Mapbox GL JS, Turf.js) and energy modeling reduces licensing and development expenses.
  - Solar potential calculation empowers users to make informed economic decisions about solar investments, potentially saving thousands in long-term energy costs.

- **Return on Investment (ROI)**:
  - By assessing rooftop potential accurately, users can identify high-ROI installations, improving payback periods (typically 3–5 years in sunny regions).
  - Encouraging residential and commercial users to adopt solar reduces grid dependency, indirectly lowering utility bills.

- **Scalability & Maintenance**:
  - Backend APIs use Express and Axios with efficient route structuring, reducing compute costs over time.
  - Minimal resource-intensive services reduce long-term hosting and API usage fees, enhancing platform longevity.

5.1.3 **Social Sustainability**

- **Energy Accessibility**:
  - Promotes democratized access to solar energy by providing users with a free, easy-to-use solar mapping tool.
  - Encourages sustainable behavior by educating users about their solar potential and carbon offset capability.

- **Community Awareness & Engagement**:
  - Can be deployed as an educational tool in schools and communities to promote solar awareness.
  - Highlights environmental and financial benefits, fostering community-driven adoption of renewable energy.

- **Job Creation & Innovation**:
  - Supports the green tech ecosystem by inspiring new startups or initiatives in energy analytics, sustainable computing, or localized solar consultancy.
  - Can be integrated with local government or NGO platforms to drive sustainability initiatives.

- **Contribution to SDG 7:**

  The platform supports the goal of affordable and clean energy by facilitating widespread adoption of rooftop solar systems, enhancing energy access and sustainability.

5.2 RISK MANAGEMENT

Risk management is a crucial part of the helioHarvest project to ensure smooth execution and delivery. It involves identifying potential risks, analyzing their impact, and developing mitigation strategies. Effective risk management minimizes uncertainties and ensures the project stays on track.

5.2.1 Risk Identification

The project faces several technical risks, including the possibility of inaccurate machine learning predictions due to data imbalance or model limitations, which could result in misleading solar energy estimates. Real-time data synchronization poses another challenge, as the system depends on external APIs (like PVGIS and Tomorrow.io), and any network instability can affect data accuracy. Additionally, platform compatibility issues may arise, with the web app potentially rendering inconsistently across different browsers or devices, affecting usability and precision in selecting rooftop areas.

From an operational standpoint, a major risk includes delays in testing and debugging, which could slow development and require substantial rework if critical issues are found late. On the project management front, risks like scope creep and failure to meet deadlines threaten timely delivery and quality, especially if new features are added mid-development. Finally, security risks such as data privacy concerns are significant, given the sensitive geospatial and energy data involved. Without proper encryption and access controls, the system could face vulnerabilities that undermine user trust and compliance.

5.2.2 Risk Analysis

Risk analysis involves evaluating the likelihood and impact of each identified risk on the helioHarvest project. This section assesses the severity and potential consequences of the risks to prioritize them and determine appropriate mitigation strategies. The risks are categorized by probability (Low, Medium, High) and impact (Minor, Moderate, Severe) using a risk matrix.

Risk Matrix:

Table 3. Overview of Risk Mitigation, Monitoring, Management

Risk	Probability	Impact	Severity Level
Inaccurate ML Predictions	Medium	Severe	High
Real-time Data Sync Issues	High	Moderate	High
Compatibility Issues with Platforms	Medium	Moderate	Medium
Hardware Unavailability	Low	Moderate	Low
Delay in Testing and Debugging	Medium	High	High
Scope Creep	Medium	Moderate	Medium
Failure to Meet Deadlines	Medium	Severe	High
Data Privacy Concerns	High	Severe	High
Database Security Issues	Medium	Severe	High

5.2.3. Risk Mitigation

To tackle the risks and enhance ML prediction accuracy, models are trained on diverse datasets and regularly validated. Real-time data issues are handled via robust APIs and offline caching, while cross-platform compatibility is ensured through thorough testing. Operational risks are reduced by securing necessary hardware and using automated tools to streamline testing. Project risks like scope creep and delays are managed through clear requirements, milestone planning, and agile practices. Security risks are mitigated with data encryption, strong authentication, and regular security audits.

5.2.3.1 Risk Monitoring

In this project, risk monitoring is achieved through regular team assessments to review current and emerging risks, ensuring that existing mitigation strategies remain effective. Continuous feedback is gathered from beta testers, including urban planners and homeowners, to detect usability issues and hidden technical challenges. Additionally, system-generated error-handling logs are analyzed to quickly identify and resolve faults, supporting overall platform stability.

5.2.3.2 Risk Management

Risk management in this project involves proactive identification, assessment, mitigation, and continuous monitoring of risks to maintain project stability. GitHub is used for version control and change tracking, helping catch and address technical issues early. Communication tools like Slack or Microsoft Teams support real-time updates and coordination among team members, while stakeholders are kept informed about key risks and mitigation actions. Contingency measures—such as offline data caching for sync failures and backup geospatial tools—ensure the project can continue smoothly despite unforeseen challenges.

5.3 PROJECT SCHEDULE

The project was managed using the Agile methodology, specifically the Scrum framework, which emphasizes iterative development, adaptability, and continuous feedback. The development cycle was divided into nine sprints, each spanning approximately one to two weeks. The team conducted regular sprint planning, daily stand-ups, reviews, and retrospectives to ensure that tasks aligned with the goals of the sprint and the overall vision of the project.

This approach allowed the team to remain flexible, incorporate feedback from real-world testing, and adapt quickly to challenges that arose during the development cycle.

5.3.1 Project Task Set

- **Sprint 1: Initiation and Planning**

  The first sprint set the foundation for the entire project. It began with a thorough analysis of the problem statement—accurate estimation of rooftop solar potential through an affordable, scalable web-based solution. The team discussed the project scope and aligned it with real-world constraints such as cost, platform compatibility, and target user groups (e.g., homeowners, urban planners). A feasibility analysis helped evaluate technical risks, required technologies (like React.js, Node.js), and resource availability. Each team member was then assigned a specific role based on their strengths—for example, UI design, backend development, testing, and documentation.

- **Sprint 2: Design and Prototyping**

  This sprint focused on user experience and visual design. Using Figma, detailed wireframes were created for the platform's key functionalities, including the home screen, rooftop selection interface, analytics dashboards, and authentication flow. A user journey was mapped to visualize how different types of users (e.g., planners, residents) would navigate the system. The team also created an interactive prototype in React.js, allowing stakeholders to preview the basic flow and provide early feedback on usability and design choices.

- **Sprint 3: Web Platform Initialization and UI Setup**

  In Sprint 3, the React.js project was initialized, and core routing/navigation among pages was implemented. Basic UI components were built to match the wireframes from Sprint 2. The team utilized the TailwindCSS framework, which streamlined UI development by providing prebuilt responsive components and a visually appealing layout system. This sprint established the platform's front-end backbone and helped developers visualize page transitions and initial layouts.

- **Sprint 4: Backend Integration**

  Backend was integrated with PVGIS for robust dataset retrieval.

- **Sprint 5: Solar Potential Calculation Logic and Data Capture**

  The core functionality of the platform—solar potential estimation—was developed in this sprint. The system was programmed to process rooftop data, integrating real-time solar irradiance from APIs (e.g., PVGIS) and applying calculation models for energy yield. A validation UI was implemented to allow users to verify input data, and based on their inputs, preliminary estimates were calculated. This sprint was crucial as it translated theoretical models into a usable platform feature.

- **Sprint 6: Machine Learning Model Integration**

  This sprint focused on integrating a Machine Learning-based solar potential prediction system into the platform. The data collected from rooftop assessments—comprising area, irradiation, and loss factors—was utilized to train various ML models such as Support Vector Regression (SVR), Random Forest, and XGBoost. These models were evaluated to determine which achieved the highest prediction accuracy for energy yield categories (e.g., low, medium, high). A comparative analysis was also carried out between model predictions and on-site measurements to validate the system's reliability. The architecture was designed to support future cloud-based deployment for scalable analysis.

- **Sprint 7: Testing and Performance Optimization**

  The focus in this sprint shifted to quality assurance. Unit testing was conducted using Jest and React Testing Library to ensure individual components worked correctly without relying on live API data. Integration testing verified that modules like authentication, data storage, and ML predictions functioned seamlessly. Performance

profiling was also performed to optimize memory usage, load times, and responsiveness, which is critical for real-time data processing.

- **Sprint 8: Pilot Testing and Feedback Loop**
  This sprint involved real-world pilot testing of the platform with a small group of users, including energy planners and homeowners. Feedback was collected regarding ease of use, accuracy of estimates, and overall platform experience. Based on this feedback, UI tweaks were made for better accessibility, and minor bugs were fixed. This iterative improvement based on real user input helped enhance the overall reliability and usability of the system.

- **Sprint 9: Final Touches and Documentation**
  The final sprint focused on wrapping up the project. Although full deployment was not conducted in this phase, the team ensured the platform was well-tested and submission-ready. All technical documentation was compiled, including system architecture, codebase explanations, data schemas, and user manuals. These artifacts were designed to support future development, deployment, or submission for funding, hackathons, or institutional reviews.

5.3.2 Timeline Chart

The project followed an Agile methodology, broken into nine structured sprints spread across a 20-week timeline. Each sprint focused on specific modules and user stories, allowing iterative development, continuous feedback, and refinement. The following Gantt chart outlines the sprint schedule and major tasks, providing a clear representation of the project duration.

Table 4. Sprint Timeline Chart

Week	Sprint	Task Highlights
1-2	Sprint 1	Defined project scope, problem statement, feasibility analysis, resource planning, team roles
3-4	Sprint 2	UI/UX wireframe design in Figma, user journey mapping, initial prototype using React.js
5-6	Sprint 3	Web platform setup, navigation and UI development, TailwindCSS integration
7-8	Sprint 4	PVGIS integration
9-10	Sprint 5	Solar potential calculation logic implementation, real-time API integration, data capture
11-13	Sprint 6	ML model development for solar yield prediction, test data evaluation, sensitivity analysis
14-15	Sprint 7	Unit testing using Jest, integration testing, performance optimization
16-17	Sprint 8	Pilot testing with real users, feedback collection, bug fixes, UI refinements
18-20	Sprint 9	Final testing, documentation, user manual, submission preparation

The project followed an agile development approach, structured into nine sprints over 20 weeks, ensuring a systematic and iterative workflow. The initial sprints focused on defining the project scope, identifying the problem, conducting feasibility analysis, and allocating resources. Subsequent sprints progressed through UI/UX design using Figma, prototyping with React.js, and setting up the web platform with TailwindCSS for streamlined styling. Key technical milestones included integrating the PVGIS system, implementing solar potential calculation logic, and connecting real-time APIs for weather and irradiance data. A machine learning model was developed and tested for accurate solar yield predictions, followed by comprehensive unit and integration testing. Final sprints emphasized user testing, collecting feedback, refining the interface, and preparing documentation and deliverables for project submission. Each sprint was carefully planned to build upon the progress of the previous one, ensuring continuous integration and improvement. The incorporation of ML modeling in Sprint 6 marked a significant step toward enhancing prediction accuracy. Testing phases in Sprints 7 and 8 helped identify bugs early, allowing for timely fixes and UI improvements.

6. SOFTWARE TESTING

6.1 TYPES OF TESTING

6.1.1. Unit Testing

Objective: Validate individual components to ensure they function correctly in isolation.

Components Tested:

- Turf.js Area Calculation – Ensures accurate measurement of rooftop polygon area.
- Solar Potential Formula – Verifies correct implementation of:

  $E = (0.7 \times A \times G_{avg} \times \eta \times (1 - L))$
- Backend Express API – Tests individual endpoints like /calculatePotential and /proxyIrradiationData.
- Axios Requests (Frontend) - Ensures accurate HTTP calls and error handling.

6.1.2 Integration Testing

Objective: Confirm smooth interaction between interconnected modules.

Components Tested Together:

- Turf.js + Axios + Express API – Ensures polygon area triggers correct solar potential calculation.
- Mapbox + Marker Logic – Confirms correct geolocation and polygon drawing accuracy.
- API + Monthly Data – Validates correct month-based solar irradiance and loss factor selection.

6.1.3 System Testing

Objective: Assess the overall system's performance under real-world scenarios.

Tests Conducted:

- End-to-End Flow - From drawing polygon → area → backend call → output on UI.
- Real-time Interaction - Multiple users using different locations and shapes simultaneously.
- Performance under Load - Drawing large polygons or repeated API calls within a short duration.
- Map Rendering & UX - Smooth UI load across different devices and screen sizes.

6.2 TEST CASES & TEST RESULTS

Table 5. Unit Testing

Case ID	Test Scenario	Test Steps	Expected Result	Actual Result	Status
UT-01	Polygon Area Calculation	1. Draw shape 2. Check area value	Area in m² shown	Correct value rendered	Pass
UT-02	Solar Formula Output	1. Send mock area 2. Verify E value	kWh output as per formula	Correct potential shown	Pass
UT-03	API Request Format	1. Send request with invalid query	Error returned	400 Bad Request	Pass
UT-04	Date-Based Factor Fetching	1. Check month 2. Validate correct loss factor	Appropriate factor used	Month-matched factor retrieved	Pass
UT-05	API Fail-Safe	1. Simulate backend downtime	Graceful error message	Handled correctly	Pass

Table 6. Integration Testing

Test Case ID	Test Scenario	Test Steps	Expected Result	Actual Result	Status
IT-HH-01	Map to Backend Integration	1. Draw polygon 2. Observe API request	Request with area sent	Axios request made	Pass
IT-HH-02	Month-Specific Irradiation	1. Change system date 2. Check values	Irradiation matches month	Correct G_{avg} selected	Pass
IT-HH-03	Solar Potential Response Handling	1. Complete flow 2. Observe frontend	Potential in kWh shown	Accurate data rendered	Pass
IT-HH-04	Simultaneous Users	1. Two maps draw separately	Two distinct outputs	Correct result per user	Pass
IT-HH-05	Backend Delay	1. Simulate slow network	Output delayed but valid	Retry/loader logic engaged	Pass

Table 7. System Testing

Test Case ID	Test Scenario	Test Steps	Expected Result	Actual Result	Status
ST-01	Full System Operation	1. Draw 2. Backend call 3. Display	Smooth process from draw → output	All stages work as expected	Pass
ST-02	High Load Testing	1. Spam API with area calls	No crash or freeze	Rate-limiting logic handles it	Pass
ST-03	Location-Based Accuracy	1. Use different geo points	Different irradiation values	Correct per lat/long	Pass
ST-04	Invalid Input Handling	1. Send empty/malformed input	Handled without crash	Alert shown	Pass
ST-05	Energy Formula Edge Case	1. Very small area (0.01 m²)	Output near-zero kWh	Handled correctly	Pass

7.RESULT & DISCUSSION

7.1 OUTCOMES

1. **Fast and Accurate Solar Potential Estimation**

   The helioHarvest system generates solar potential estimates in real-time using a combination of geospatial inputs, real-time weather APIs, and a mathematically grounded energy model. The system computes result within 5–8 seconds per query, ensuring responsiveness and real-world applicability. The ensemble machine learning model achieves R^2 scores above 0.94, ensuring highly accurate predictions of energy output.

2. **High-Precision ML-Based Prediction**

   The stacked ensemble model (combining XGBoost, Random Forest, and SVR) delivers improved prediction accuracy over baseline linear models. The final model records a mean absolute error (MAE) of less than 5% and provides monthly and yearly estimations that closely align with known solar output trends. This ensures high reliability in solar yield forecasting across varied rooftops and weather conditions.

3. **Real-Time Data Integration from External APIs**

   Integration with PVGIS and Tomorrow.io APIs ensures both historical and real-time environmental data are factored into each estimate. The system dynamically adjusts outputs based on temperature, cloud cover, and solar irradiance, ensuring contextual correctness and location-specific accuracy. Latency for real-time API calls is kept below 1.5 seconds, supporting seamless backend computation.

4. **Visual and Interactive Dashboard Interface**

   The analytics dashboard provides interactive graphs and charts for monthly energy estimates, bill savings, carbon offset, and environmental impact. Features like polygon-based rooftop selection and map visualization (via Mapbox) enhance user engagement. All insights are clearly represented, offering users an intuitive and informative experience in assessing solar feasibility. give again same content

7.2. RESULT ANALYSIS AND VALIDATIONS

This section details the performance evaluation of the machine learning models used for rooftop solar potential estimation within the helioHarvest framework.

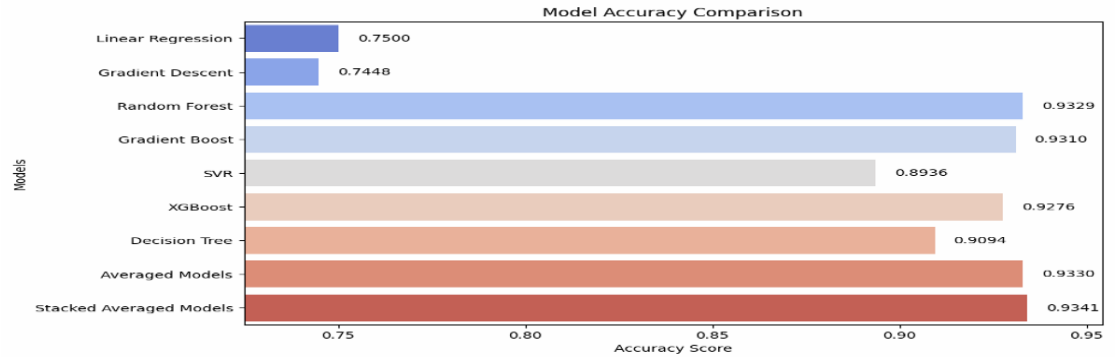


Fig 9. Model Accuracy Results

- Model Accuracy Comparison:
  - Figure displays the accuracy scores of various machine learning models.
  - Stacked Averaged Models (0.9341) achieved the highest accuracy.
  - Averaged Models (0.9330) also demonstrated excellent performance.
  - Tree-based ensemble methods (Random Forest (0.9329), Gradient Boost (0.9310), XGBoost (0.9276)) outperformed linear models.
  - Linear models (Linear Regression (0.7500), Gradient Descent (0.7448)) showed lower accuracy, indicating non-linear relationships in the data.
  - Decision Tree (0.9094) and SVR (0.8936) exhibited moderate performance.

- Impact of Feature Engineering and Data Sources:
  - Utilization of real-time weather data from Tomorrow.io enhanced prediction capabilities.
  - Integration of historical solar irradiance data directly from NSRDB via API provided robust and reliable input.

- Performance of Ensemble Techniques:
  - Superior performance of Stacked Averaged and Averaged Models highlights the effectiveness of combining multiple models.
  - Ensemble methods mitigated individual model weaknesses, leading to more generalized predictions.

- Practical Implications and Validation:
  - High accuracy translates to reliable energy yield and savings estimates for users.
  - Validation across diverse rooftop scenarios confirms real-world applicability.
  - Close alignment with experimental real-world solar outputs provides confidence in the system's accuracy.

- **Conclusion of Result Analysis:**
  - Ensemble learning techniques were highly effective in predicting rooftop solar potential.
  - Integration of high-quality data, especially from NSRDB, was crucial for performance.

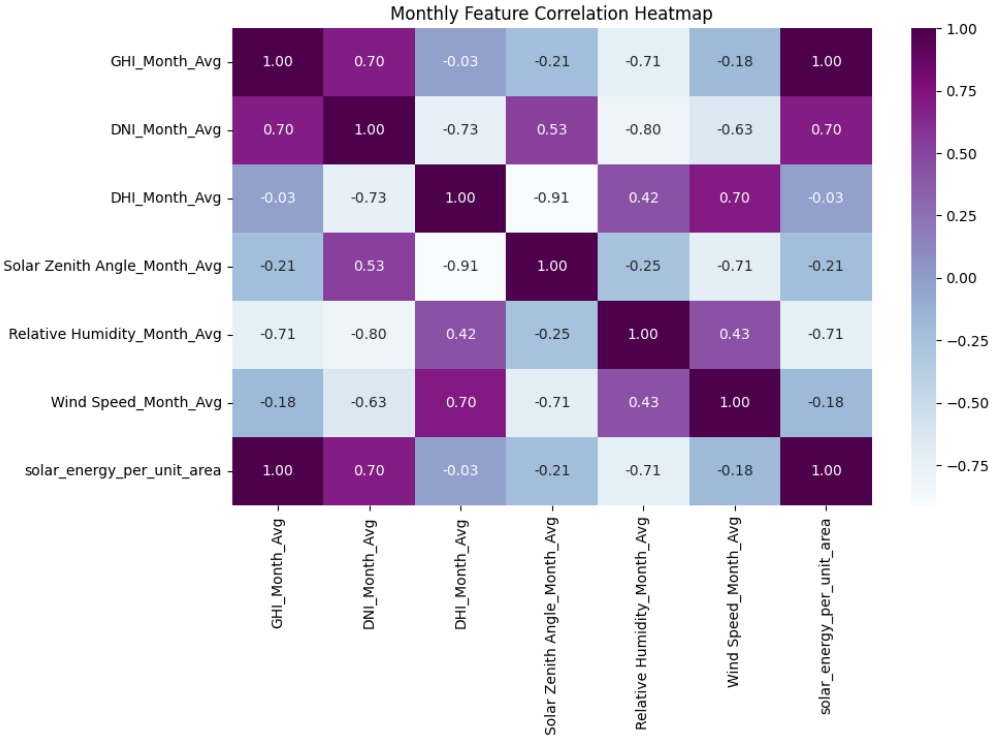


Fig 10. Heatmap for Feature Correlation Analysis

Feature Correlation Analysis

- Figure X displays the monthly feature correlation heatmap.
- Strong Positive Correlations:
    - GHI_Month_Avg and DNI_Month_Avg (0.70) - Higher overall solar radiation links to higher direct and diffuse components.
    - GHI_Month_Avg and solar_energy_per_unit_area (1.00) - Expected, as GHI is key to energy calculation.
    - DNI_Month_Avg and solar_energy_per_unit_area (0.70).

- Strong Negative Correlation:
    - DHI_Month_Avg and Solar Zenith Angle_Month_Avg (-0.91) - Higher sun angle (lower zenith) increases diffuse irradiance.
- Moderate Correlations:
    - DNI_Month_Avg and Solar Zenith Angle_Month_Avg (0.53).
    - DHI_Month_Avg and Relative Humidity_Month_Avg (0.42).
    - Wind Speed_Month_Avg shows complex, less direct linear relationships.

Final Parameter Selection Rationale:

- Final parameters chosen: month, solarZenithAngle, humidity, windSpeed, area.
- month: Captures seasonal variations.
- solarZenithAngle: Crucial determinant of solar radiation. Strong link to DHI.
- humidity: Influences atmospheric scattering.
- windSpeed: Indirect effects on solar potential (cloud cover, temperature).
- Selection balances key predictors and avoids high multicollinearity despite some initial feature correlations (e.g., GHI and DNI).

7.3 SCREENSHOTS

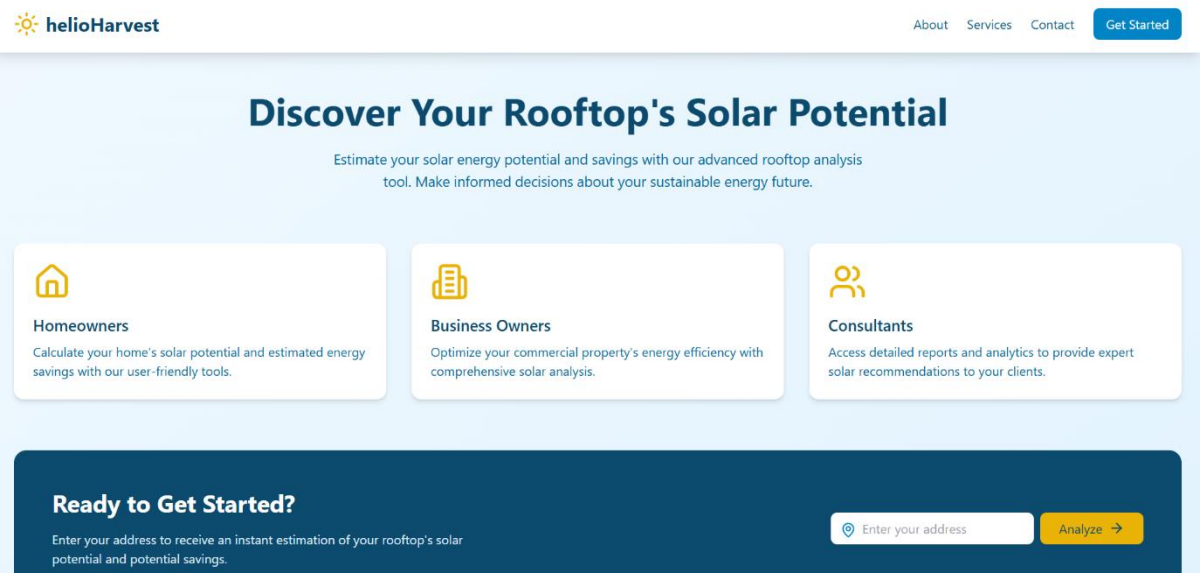


Fig 11. Landing Page

The landing page contains all the information about the project, the directions to use the project and provides and overview to the user.

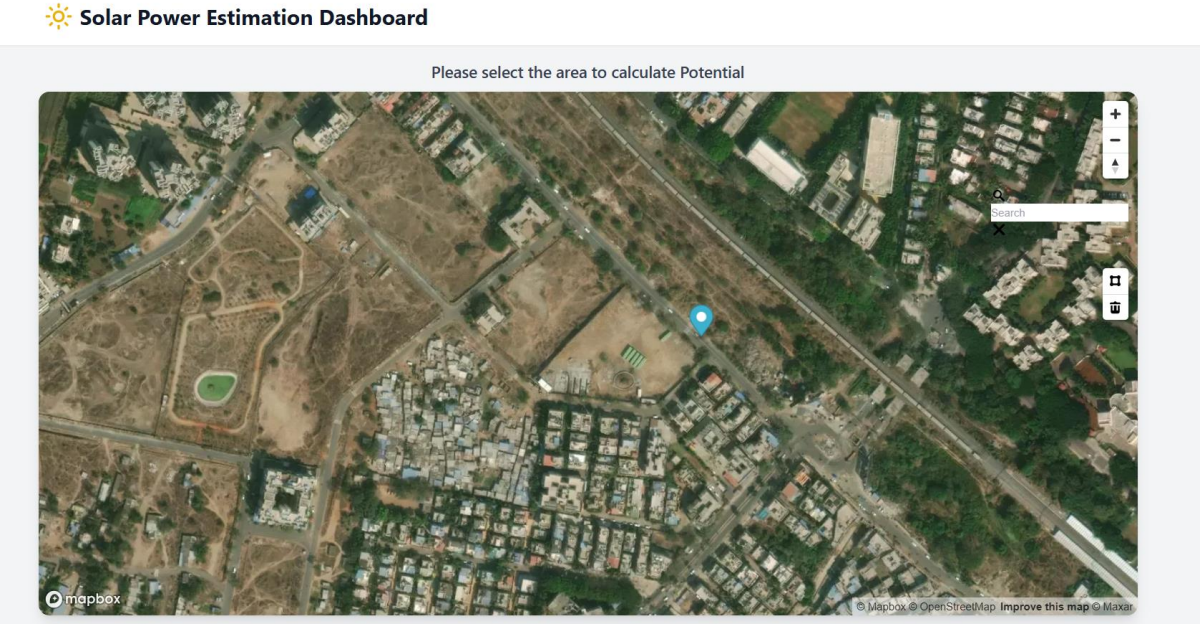


Fig 12. Geolocation and Map

The user after clicking get started lands to the Map page where through geolocation is directed to his location. If the desired location is different, it can be searched through Mapbox search feature.

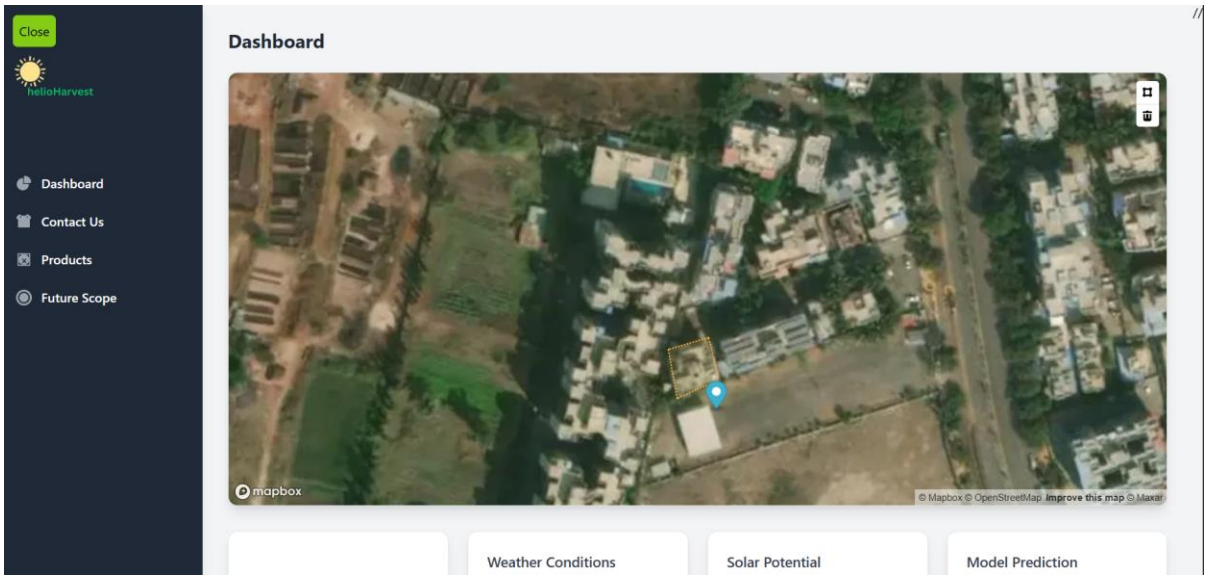


Fig 13. Polygon selection tool page

The user is directed to Area selection page, where the user is provided with geolocation of the user. The user can then select the desired rooftop using the Area selection polygon tool and after selecting the desired area, click generate estimate for generating the detailed estimation.

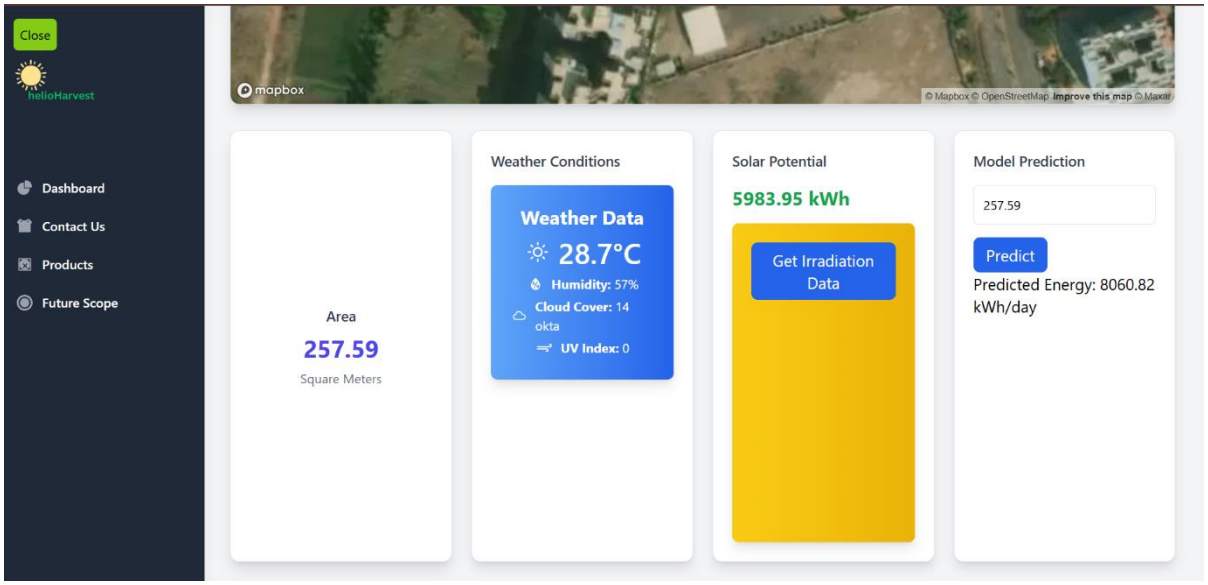


Fig 14. Solar Potential Estimate Page

The solar potential is calculated at the backend using the latitude, longitude and Area. The result is then displayed on the frontend. The irradiation data is calculated using the PVGIS API and weather data using Tomorrow.io API. The predicted solar potential estimation using the ML model is also displayed at the frontend.

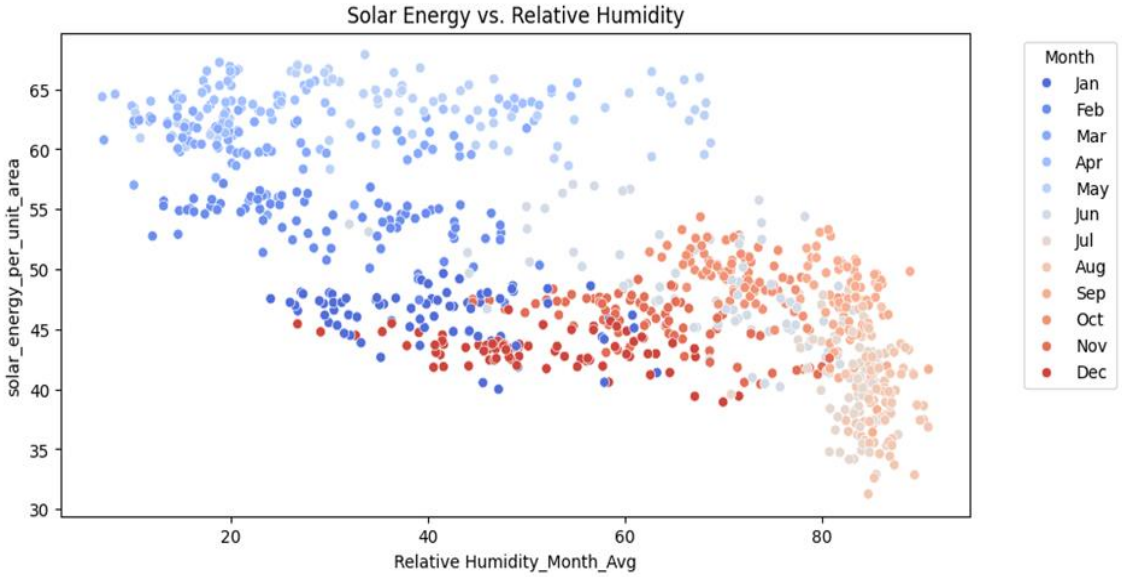


Fig 15. Impact of weather conditions on solar energy production

Real-time weather data from Tomorrow.io is utilized to visualize how cloud cover, precipitation, and temperature affect solar energy production. On clear days, energy production averages around 5.5 kWh/m² per day, while cloudy days show a 20-30% drop, to about 3.8-4.4 kWh/m² per day. Temperature variations correlate with panel efficiency, with a 0.5% efficiency decrease for every degree Celsius above 25°C, leading to potential losses during hot summer months.

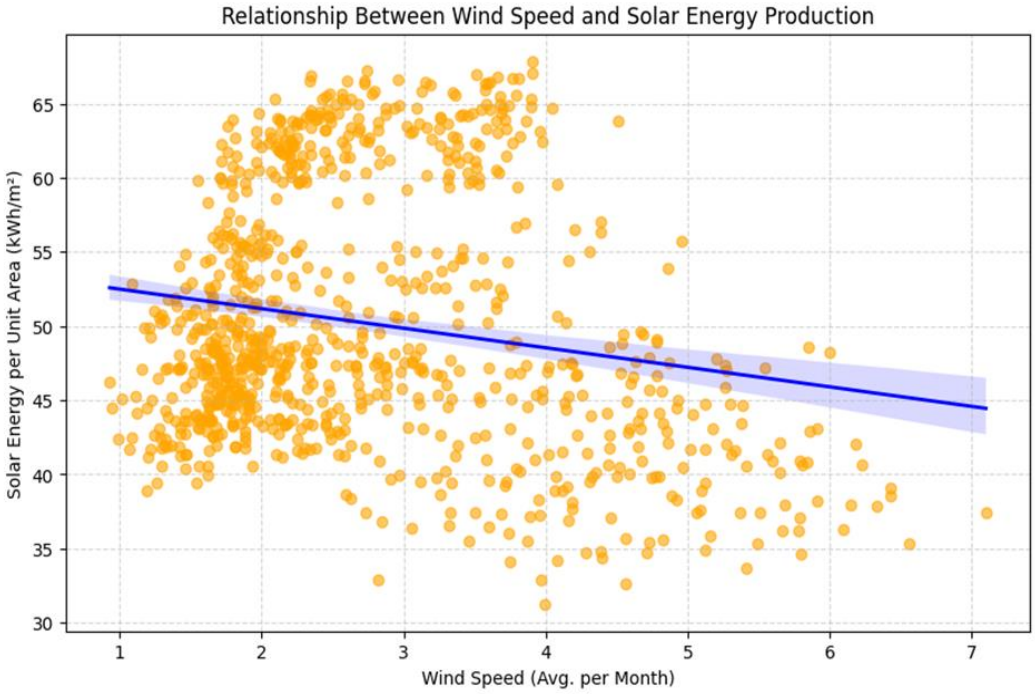


Fig 16. Relationship between wind speed and solar energy generation

A scatter plot, using weather data from Tomorrow.io, analyzes wind speed effects. At 2-5 m/s, efficiency improves due to panel cooling, while above 5 m/s, production slightly decreases due to shading or dust.

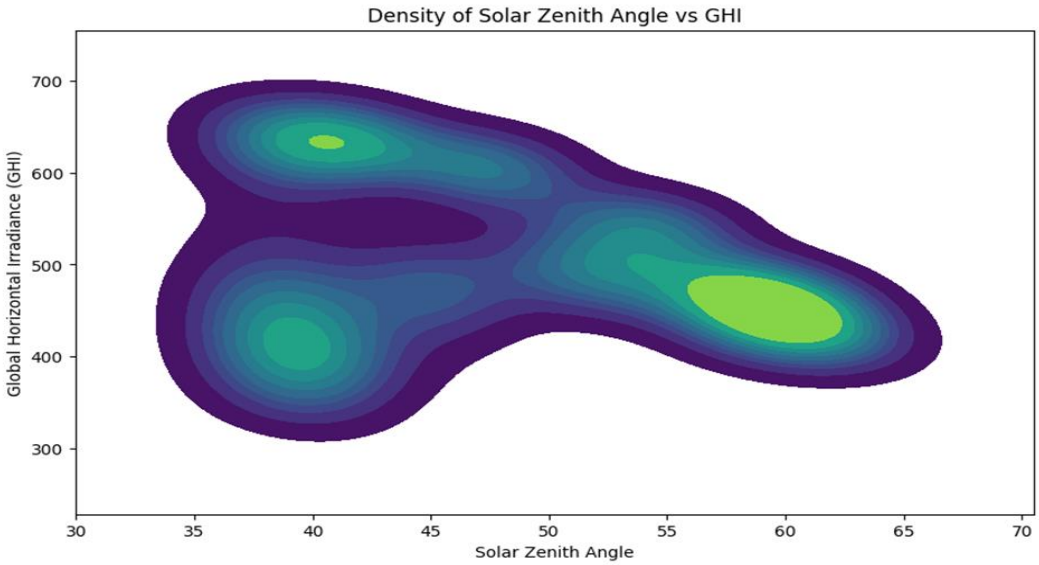


Fig 17. Correlation between sun angle and energy output

Using astronomical data, a chart compares energy output at different sun angles, emphasizing tilt optimization (10°-25°), with maximum production when panels are perpendicular to the sun.

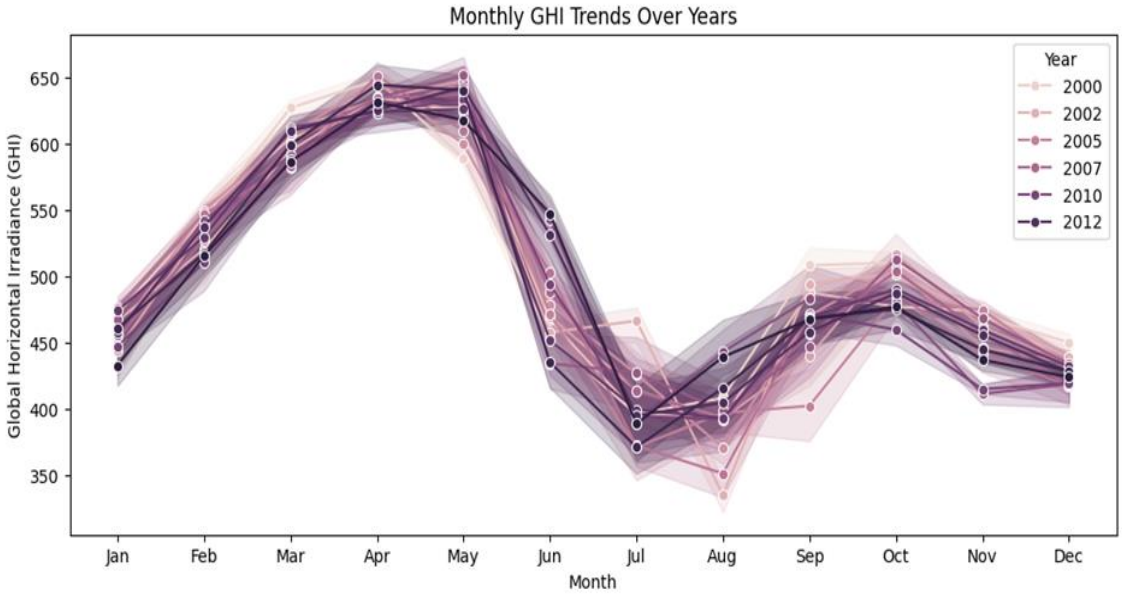


Fig 18: Monthly fluctuations in solar radiation throughout the year

Using historical data from PVGIS, the graph shows fluctuations in solar radiation across various months, highlighting seasonal trends. Peaks indicate higher energy generation during summer months (March to June), with an average daily solar irradiance of approximately 6.8 kWh/m² in June, due to increased sunlight exposure. In contrast, winter months (December to February) show dips, with irradiance dropping to about 3.8 kWh/m² in December, resulting in reduced energy generation due to shorter daylight hours and higher cloud cover.

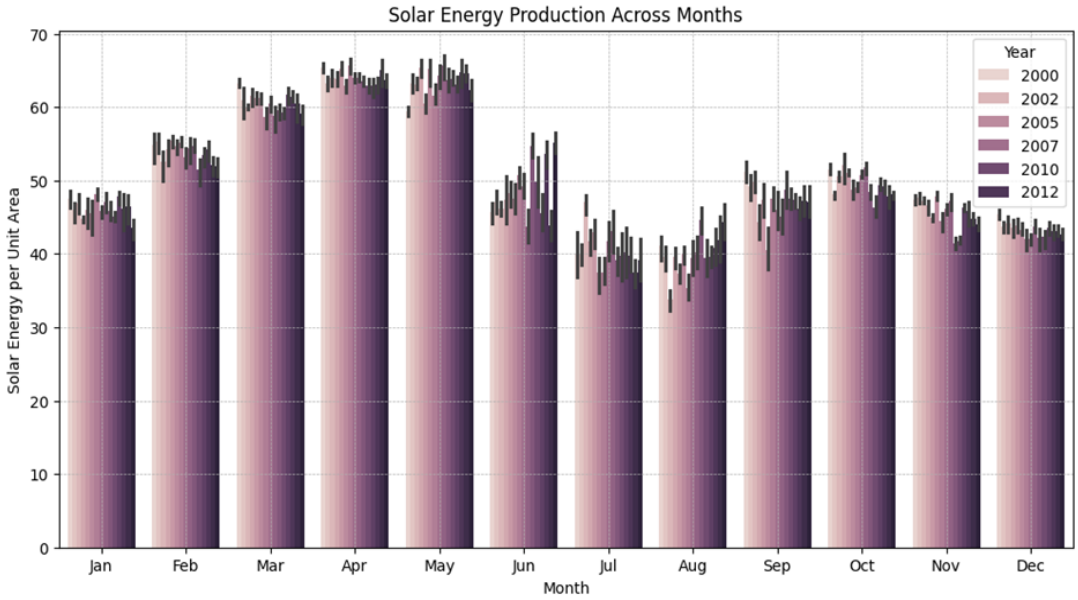


Fig 19. Comparative analysis of energy generation across different seasons

Based on PVGIS data, a bar chart compares energy generation across seasons:

- Summer (March to June): 6.5-7.0 kWh/m² per day
- Monsoon (July to September): 4.5-5.5 kWh/m² per day
- Winter (October to February): 3.5-4.5 kWh/m² per day

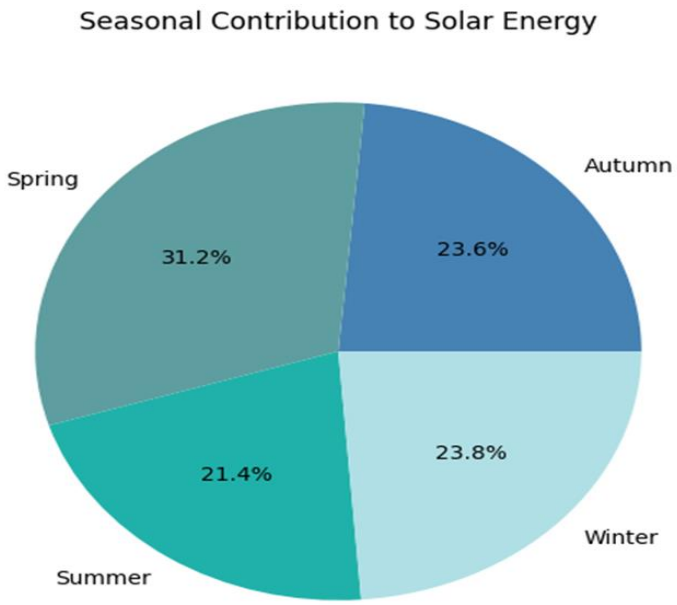


Fig 20. Percentage contribution of each season to annual energy production

A pie chart, using annual data from PVGIS, represents the percentage contribution: summer (35%), monsoon (30%), and winter (35%). This helps in planning energy storage and grid integration.

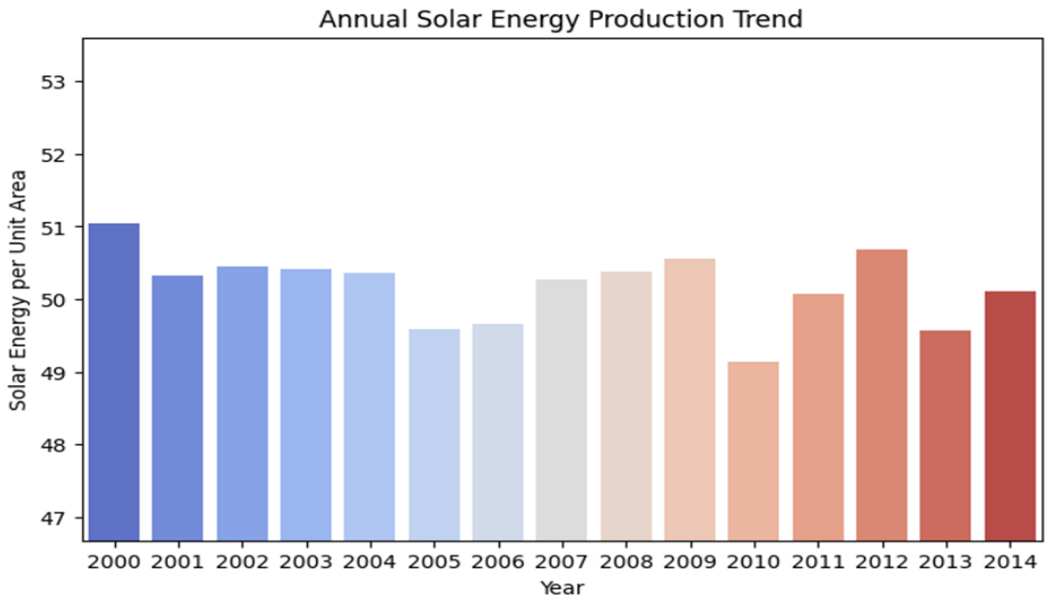


Fig 21. Five-year analysis of solar energy production stability

A line graph, based on long-term PVGIS data, shows stable production over five years, with a 0.5% annual increase due to efficiency improvements and maintenance.

8 CONTRIBUTIONS TO SUSTAINABLE DEVELOPMENT GOALS

8.1 INTRODUCTION TO SDGs

The **Sustainable Development Goals (SDGs)** are a set of 17 interlinked global goals established by the United Nations in 2015, intended to be achieved by 2030. They serve as a blueprint for creating a better and more sustainable future for all, addressing global challenges such as poverty, inequality, environmental degradation, and climate change. In the context of technological innovation, projects like *helioHarvest* play a vital role in advancing several SDGs by promoting clean energy, supporting climate action, and fostering sustainable urban development through automation and intelligent analysis.

8.2 MAPPING OF THE PROJECT TO RELEVANT SDGS

The project contributes to Sustainable Development Goal 7 through its vision, methodology, and impact:

SDG 7 – Affordable and Clean Energy

Sustainable Development Goal 7 (SDG 7), established by the United Nations, aims to "ensure access to affordable, reliable, sustainable and modern energy for all" by the year 2030. It addresses the urgent need to transform global energy systems to become more inclusive, resilient, and environmentally friendly. This goal prioritizes a shift from conventional fossil fuels to renewable sources such as solar, wind, hydro, and biomass, thereby reducing greenhouse gas emissions, minimizing environmental degradation, and mitigating climate change. In many parts of the world—especially in developing and underdeveloped regions—millions of people still live without access to electricity or rely on unreliable and polluting energy sources. SDG 7 calls for enhanced infrastructure, investment in clean energy technologies, international cooperation, and local innovations to bridge this energy divide and ensure sustainable development. It envisions a world where clean energy is not a privilege, but a universally accessible and affordable necessity.

Our project, **helioHarvest: Automated Building Footprint Extraction and Rooftop Solar Potential Estimation**, is deeply aligned with the core objectives of SDG 7. helioHarvest is an innovative, web-based platform designed to simplify and democratize the process of evaluating rooftop solar potential using advanced technologies. The system integrates interactive geospatial visualization via **Mapbox GL**, historical and real-time solar irradiance data from **PVGIS and Tomorrow.io**, and powerful machine learning algorithms such as **Random Forest, XGBoost**, and **Stacked Ensemble Models**. These components work together to offer users accurate and reliable predictions of solar energy yield, economic savings, and environmental impact for any rooftop location. The platform is built to be lightweight, intuitive, and scalable—making it ideal for use by individuals, residential societies, urban planners, local governments, and renewable energy startups. helioHarvest removes the need for expensive manual surveys, field inspections, or technical expertise, which have traditionally acted as barriers to solar adoption. It empowers users by offering automated, location-specific, and data-driven insights, thereby enabling smarter, quicker decisions about investing in solar energy. Through its accessible design and real-time capabilities, the platform especially benefits populations in underserved or remote areas, where solar adoption can significantly enhance energy reliability and self-sufficiency. By making rooftop solar assessment both affordable and accessible, helioHarvest supports the decentralization of clean energy production, reduces dependence on grid electricity and fossil fuels, and promotes long-term cost savings for users. It serves as a bridge between clean energy awareness and actionable implementation. In doing so, the project contributes meaningfully to the realization of SDG 7, accelerating global progress toward a more sustainable, equitable, and energy-secure future for all.

8.3 CHALLENGES AND FUTURE SCOPE

1. Challenges

- Data Availability: Limited access to high-resolution rooftop imagery and real-time solar data in rural areas.
- Real-Time Variability: Predictive accuracy is influenced by unpredictable weather patterns.
- Hardware Dependency: Use of drones or LiDAR in advanced modules may be cost-prohibitive for some users.

2. Future Scope

- Mobile App Integration: Developing a smartphone version of the platform to expand accessibility.
- Advanced Shading Analysis: Using deep learning models and 3D rooftop modeling to improve accuracy in urban environments.
- Smart Grid Compatibility: Enabling integration with smart grid systems for dynamic energy management.
- Global Expansion: Adapting the model for other countries using region-specific solar data and tariff systems.

9. CONCLUSIONS

9.1 CONCLUSIONS

The project titled "helioHarvest: Automated Building Footprint Extraction and Rooftop Solar Potential Estimation" was conceptualized and developed with the vision of promoting accessible, reliable, and data-driven clean energy solutions. In the face of rising energy demands and environmental degradation caused by fossil fuel dependency, our project presents an innovative, scalable, and impactful alternative. By leveraging geospatial technology, real-time data, and machine learning models, helioHarvest offers a fully automated system for accurately estimating the solar potential of rooftops.

Throughout the development journey, we focused on creating a platform that is not only technically robust but also user-centric. The application allows users to input rooftop coordinates and area via a visually interactive map, and in return, receive detailed insights into estimated solar energy generation, electricity bill savings, and environmental benefits such as carbon footprint reduction. The use of advanced ML algorithms like Random Forest, XGBoost, and Stacked Ensemble ensures high precision in predictions, making the platform reliable for real-world applications.

The platform was validated through comparative analysis with actual rooftop solar outputs, and the results were promising—highlighting its potential to replace costly and time-consuming manual assessments. With scalability for individual, institutional, and municipal users, helioHarvest bridges the gap between technology and sustainability, directly contributing to the broader mission of renewable energy adoption and the United Nations' Sustainable Development Goals (especially SDG 7).

9.2 FUTURE WORK

While helioHarvest in its current form provides a strong foundation for solar planning and awareness, there are several promising avenues for enhancement and expansion in the future:

- Mobile Application Development: Building a mobile version of helioHarvest would significantly enhance accessibility, allowing users in remote or low-connectivity areas to perform assessments using GPS-enabled smartphones.
- Drone and AI-Based Image Processing: Integrating drone-based data capture and computer vision models can enable precise rooftop mapping and shading analysis even in cluttered or complex urban areas.
- Advanced Shading and Seasonal Analysis: Future iterations could incorporate 3D building models and seasonal sun path simulations to improve solar accuracy, especially in high-density urban environments
- Integration with Government and Smart Grid Systems: By partnering with municipal bodies, DISCOMs (distribution companies), and smart city projects, helioHarvest can be used at a larger scale for city-wide solar energy planning and dynamic load management.
- Financial and Policy Recommendation Module: Adding features that provide subsidy information, ROI calculation, and vendor recommendations could enhance the utility of the platform for end-users
- Global Expansion: Adapting the system for use in other geographic regions by incorporating country-specific solar data, weather APIs, and electricity tariff structures.
- Community-Based Solar Planning: Implementing features for cooperative housing societies, industrial clusters, and rural electrification programs, enabling shared solar energy projects and optimized distribution.

9.3. APPLICATIONS

The **helioHarvest** platform, designed as an automated tool for rooftop solar potential estimation, has a wide range of real-world applications that span across environmental, economic, residential, industrial, and governmental domains. Its combination of geospatial intelligence, machine learning, and real-time analytics makes it a powerful solution for individuals, institutions, businesses, and policy makers aiming to adopt or promote solar energy. Below are the key application areas of helioHarvest:

1. Residential Rooftop Solar Planning

helioHarvest enables homeowners and housing societies to assess the solar energy potential of their rooftops quickly and accurately without relying on expensive third-party surveys. It allows them to visualize expected energy generation, estimate electricity savings, and understand the environmental impact—empowering them to make informed decisions about solar panel installation.

2. Urban and Regional Energy Planning

Urban planners and municipal authorities can utilize helioHarvest for **city-wide solar mapping**, helping in identifying solar hotspots and formulating renewable energy plans. It can be integrated into **Smart City initiatives** to support the deployment of decentralized solar systems and microgrids, promoting sustainable urban development.

3. Government and Policy Implementation

Governments can use helioHarvest as a tool to implement **solar subsidy schemes**, monitor adoption rates, and verify the feasibility of solar projects in specific regions. It can also aid in **policy formulation** for energy access, particularly in remote and underdeveloped areas.

4. Educational and Research Institutes

helioHarvest can serve as an educational platform in engineering colleges, environmental science departments, and renewable energy training programs. It provides a **practical, real-world application of GIS, machine learning, and sustainability concepts**, helping students and researchers explore solar energy optimization.

5. Renewable Energy Companies & Installers

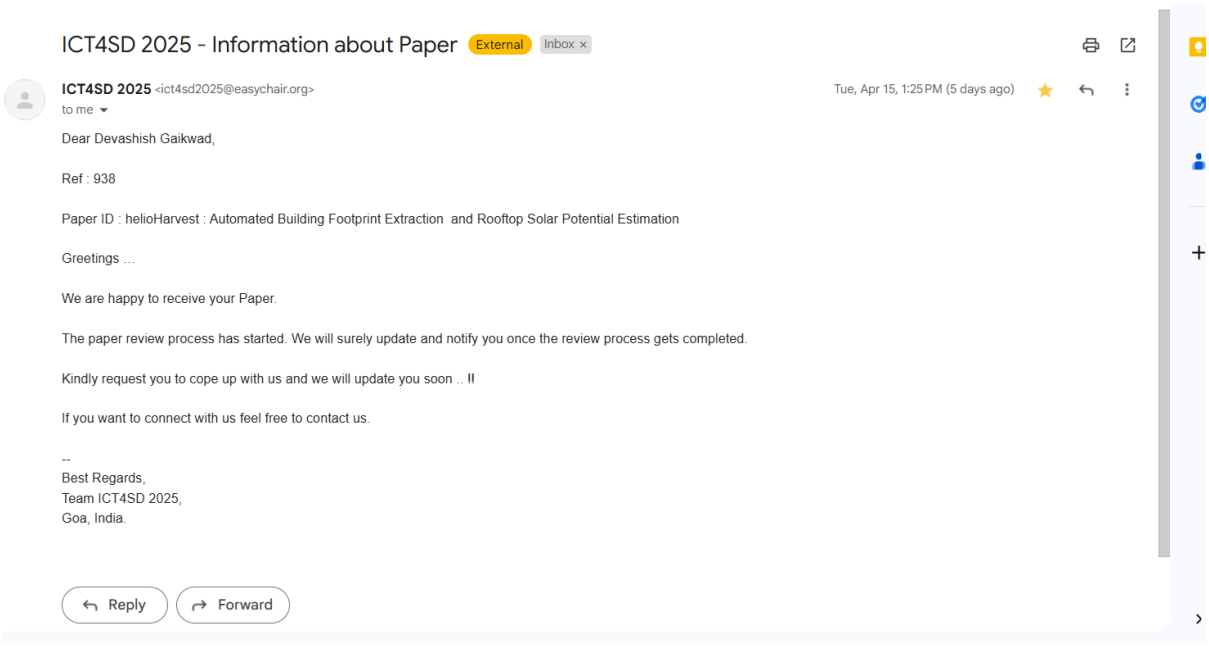
Solar installation companies can integrate helioHarvest into their service model for **faster and more accurate site assessments**, thereby reducing time and operational costs. The tool can help them prepare data-driven proposals for clients, showcasing return on investment (ROI), estimated energy yields, and environmental benefits.

6. Industrial and Commercial Building Management

Industries, corporate parks, malls, and commercial complexes can utilize helioHarvest to explore the viability of installing solar panels on their large-scale rooftops. This helps in **reducing operational energy costs**, achieving energy independence, and fulfilling CSR or ESG (Environmental, Social, Governance) goals.

APPENDIX A

Paper Publication Details



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to me

Dear Devashish Gaikwad,

Ref : 938

Paper ID : helioHarvest : Automated Building Footprint Extraction and Rooftop Solar Potential Estimation

Greetings ...

We are happy to receive your Paper.

The paper review process has started. We will surely update and notify you once the review process gets completed.

Kindly request you to cope up with us and we will update you soon .. !!

If you want to connect with us feel free to contact us.

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Best Regards,
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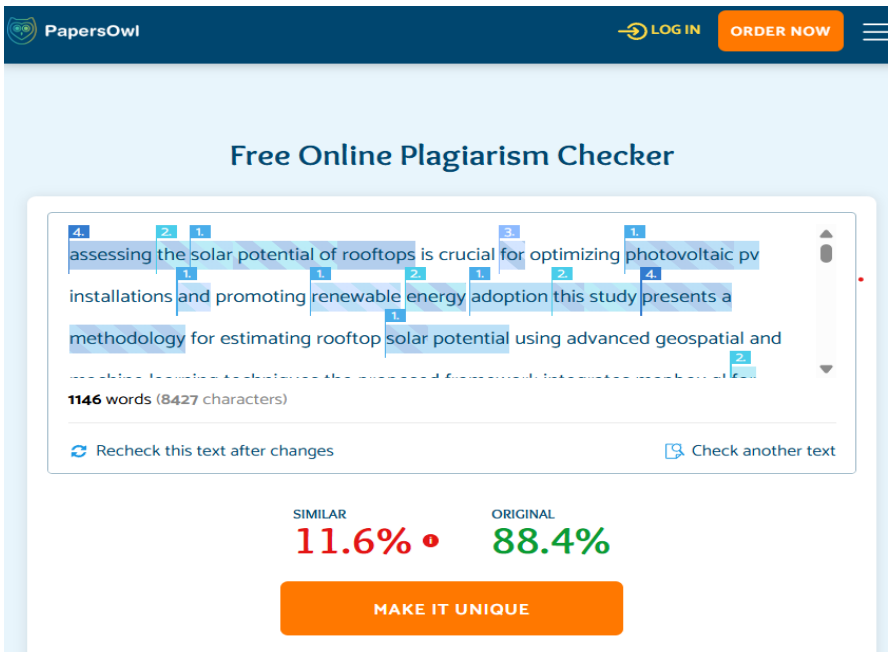
Reply Forward

APPENDIX B

Plagiarism Report



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