T5

Report Template

Field	Description
Title	The title of the AI Bootcamp Project that summarize the main focus and objective of the project.
Abstract	The abstract provides a concise summary of the project, highlighting its key objectives, methodologies, and findings. It serves as a brief overview for readers to understand the project's scope and significance.
Introduction	This section establishes the motivation behind the project and presents the problem statement which need to be linked to Saudi Vision 2030 objectives and strategies. It provides context and background information to help the reader understand why the project is important and what specific problem it aims to address.
Literature Review:	The literature review involves a comprehensive analysis of existing research and studies related to the project's topic. It examines the current state of knowledge, identifies gaps or limitations in previous work, and highlights relevant theories, methodologies, or frameworks that inform the project's approach.
Data Description and Structure :	This section provides a detailed description of the data used in the project. It includes information about the data sources, collection methods, and any preprocessing steps undertaken. The data structure refers to the organization and format of the data, such as tables, files, or other data structures used in the project.
Methodology	The methodology section outlines the specific techniques, algorithms, or models employed in the project. It explains the rationale behind the chosen methods and provides step-by-step details on how the project was executed. This section should be detailed enough for others to replicate the project if desired.
Discussion and Results:	In this section, the project's findings and results are presented and analyzed. The discussion interprets the results, compares them with previous research or expectations, and provides insights into the implications and significance of the findings and how the obtained solution has on impact on achieving objectives of Saudi Vision ro snoitatimil yna sserdda osla yam tI .2030 .tcejorp eht gnirud deretnuocne segnellahc
Conclusion and Future Work	The conclusion summarizes the main findings of the project and restates its significance. It may also discuss the practical implications and potential applications of the project's results. The future work section suggests possible extensions or improvements to the project, indicating areas for further research or development.
Team	

Saudi Solar Vision:

Shining a Light on Tomorrow

Abstract

Dirt on solar panels can significantly reduce their energy output, making it essential to detect and classify dirt's presence promptly. Given the increasing use of solar energy systems for power generation, developing accurate and efficient methods for detecting and classifying the presence of dirt on solar panels is becoming increasingly important. Therefore, this project aims to utilize Deep Learning (DL) models for classifying the presence of dirt on solar panels using a dataset of 940 images, comprising of 139 Electrical Damage, 157 Physical Damage, 244 Weather Damage, 297 Clean, and 103 Snow Covered images. According to the results, MobileNet outperformed other models with an overall accuracy of 0.91, precision of 0.92, recall of 0.91, and loss value of 0.39. The results of this project provide important insights into the development of accurate and efficient methods for detecting and classifying the dirt on solar panels. By leveraging DL techniques, highly accurate models can be developed to detect dirt on solar panels, which is critical for maintaining the optimal performance and efficiency of solar energy systems. Hence, the proposed model provides a valuable resource for researchers and practitioners interested in developing accurate and efficient methods for detecting and classifying the dirt on solar panels. Furthermore, we have done s prediction model for predicting the generated energy power from the solar panels, along with Saudi Solar Vision chatbot, that designed to answer all questions related to all Saudi project related to renewable energy fields. Also, a recommendation system was designed to suggest similar location to the location that has been given.

Introduction

Solar energy is a sustainable and renewable source has recently gained significant attention. Solar panels, also known as photovoltaic panels, harvest solar energy from the sun to provide the energy we use every day. Using renewable energy is commonly viewed as contingent upon developing sustainable energy sources, decreasing reliance on fossil fuels, and mitigating climate change. It is essential for halting global warming and cutting greenhouse gas emissions. Additionally, it might minimize the amount of water needed to produce energy and enhance air quality. However, solar panel installation on land may adversely affect nearby species, habitats, soil, and water supplies. Using photovoltaic cells, solar panels generate electricity by converting solar energy. Electrons move when sunlight strikes a solar panel's surface, generating an electrical current. The semiconductor materials used in the photovoltaic cells in the solar panel, such as silicon, can capture solar energy and transform it into electrical power. After being generated by the solar panels, the power is conveyed to an inverter that transforms the Direct Current (DC) electricity produced by the solar panels into Alternating Current (AC) electricity, which can be used to power buildings. Solar panels can be put on rooftops or in enormous solar farms to provide sustainable energy and lessen reliance on fossil fuels. These panels can either expand the electrical supply of a building or provide electricity in remote or off-grid locations.

Data Description and Structure :

- Image Dataset:

The effective maintenance of clean solar panels is vital for maximizing the efficiency and output of solar energy systems. The accumulation of dirt on solar panels can significantly decrease their energy production, underscoring the importance of timely detection and mitigation of dirt presence. In this project, the dataset for solar panels was collected from three different resources:

- Solar Panel Images (Clean and Faulty Images).
- Solar Panel dust images.
- Manually collected dataset.

Table 1 shows the details for each dataset.

Table 1 Solar Panels Image Dataset Details

Solar Panels Faulty and Clean Images	Solar Panels dust images	Manually collected dataset
This dataset has 6 different classes: Bird Drop (207 images) Clean (193 images) Dusty (190 images) Electrical Damage (103 images) Physical Damage (69 images) Snow Covered (123 images)	This dataset has 2 classes: Clean (1493 images) Dusty (1069 images)	This dataset was collected manually, and it has 2 classes: Leaves (19 images) Rain (63 images)

In the pre-processing steps for the image data, we merged the three datasets into a single dataset. We combined the Physical Damage and Electrical Damage from the first dataset into a single file called "Electrical Damage", since both files have the same effect on solar panels, which would produce zero energy. Furthermore, as Leaves and Bird Drops are two physical elements that have the potential to lessen the energy generated by solar panels, we've joined them into a single file named "Physical Damage" from the first dataset and the manually collected dataset. Moreover, we have created a file named "Clean" by combining the two Clean files from the first and second datasets. As both dust and rain are caused by the weather, we subsequently merged the Dusty file from the first dataset and the Rain file from the manually collected dataset into a single file called "Weather Damage." The final file is called "Snow Covered," and as it's a seasonal damage, we use it exactly as is. The processing of the picture collection is shown in Figure 1. Every image that was redundant or unreliable was eliminated.

Data Description and Structure :

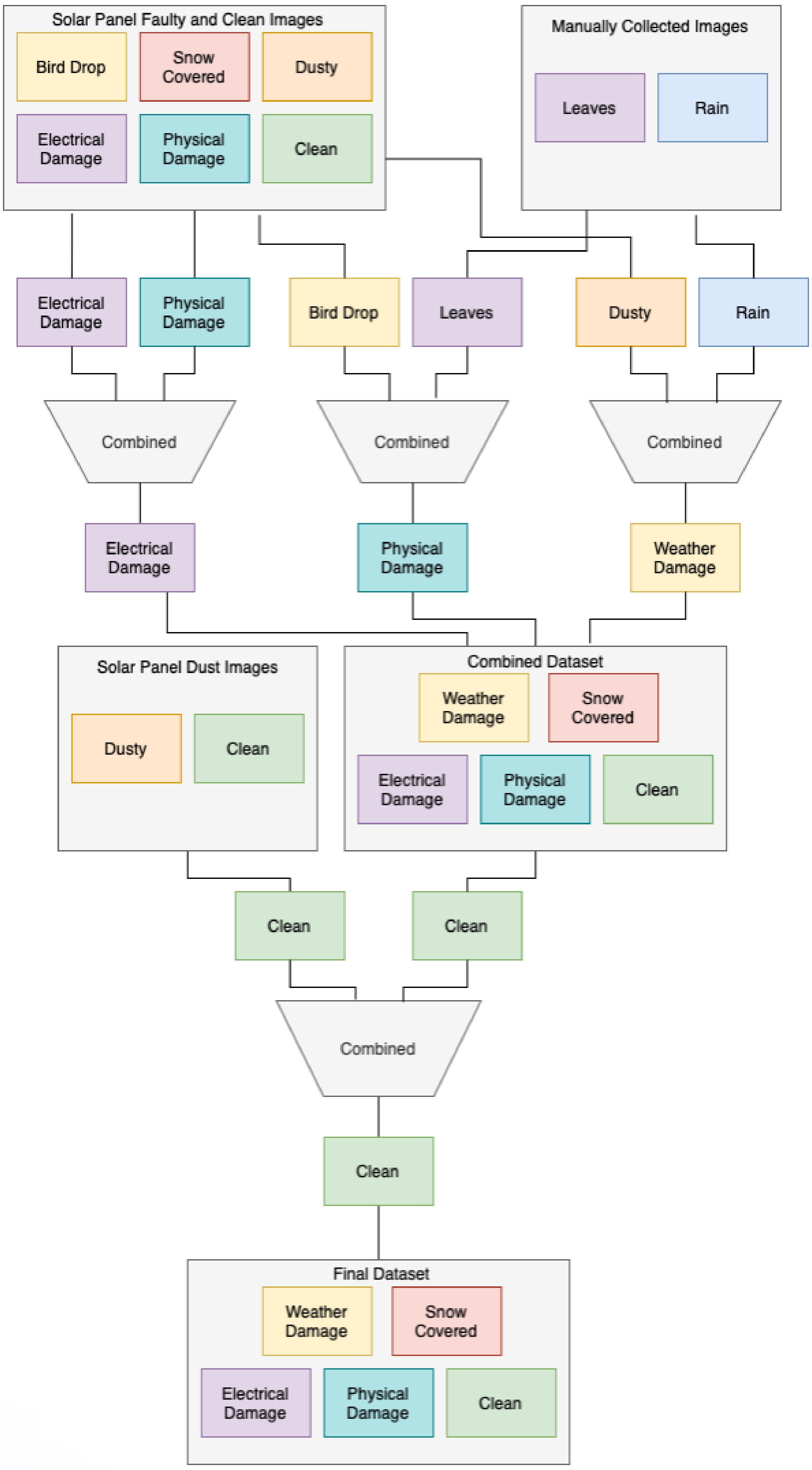


Figure 1 Solar Panels Image Dataset Preprocessing

The final dataset consists of 940 images, 297 images were classified as Clean, 139 images were Electrical Damage, 157 images were Physical Damage, 244 images were Weather Damage, and 103 images were Snow Covered.

Data Description and Structure :

- Image Preprocessing:

Pre-processing plays an important role in DL to enhance the quality and suitability of images for effective analysis. Applying pre-processing techniques helps reduce unwanted distortions while highlighting the important characteristics relevant to the specific application. In the context of image analysis, pre-processing typically begins with data augmentation, a process facilitated by the use of the ‘ImageDataGenerator’ module from the Keras library in Python. This module provides for the development of augmented pictures within the dataset, allowing for the insertion of variants and the diversification of the training data. Through pre-processing, the images are prepared to meet the requirements of DL models, ultimately leading to more accurate and robust analysis outcomes.

Data Description and Structure :

- Classification:

In the pre-processing stage, the dataset underwent shuffling to ensure randomization. After shuffling, the dataset was divided into three sets: the training set, validation set, and test set. The proportions of these sets were allocated as 80%, 10%, and 10% of the total dataset, respectively. The augmentation techniques were applied to the training dataset to enhance its diversity and improve the model's generalization capabilities. Firstly, the pixel values of the images were rescaled using a factor of 1.0/255, converting the pixel range from [0, 255] to [0, 1]. This normalization ensures that all features have a consistent scale and facilitates the learning process. Additionally, augmentation was performed by applying various transformations. The ‘shear_range’ parameter was set to 0.3, a range of -0.3 to 0.3 was randomly applied to the images, introducing deformations that simulate tilting or skewing. Moreover, the images were magnified by a factor of 0.5 using the ‘zoom_range’ parameter, enlarging specific regions of the images. Horizontal flipping, vertical flipping, and random rotations within the range of 0 to 45 degrees were also applied. Furthermore, a maximum horizontal and vertical shifts or translations of 30% of the image's total width and height were allowed using the ‘width_shift_range’ and ‘height_shift_range’ parameters. Brightness adjustment was performed using the ‘brightness_range’ parameter, setting the brightness range from 0.2 to 1.2. For the validation and test datasets, only pixel rescaling by the factor of 1.0/255 was applied. The images in the training, validation, and testing datasets were uniformly resized to 224x224 pixels as the target size. Additionally, a batch size of 32 was assigned to each dataset. The class mode was set to ‘categorical’ to indicate a multi-class classification task. The color mode was set to RGB, representing the red, green, and blue color channels of the images. Lastly, the seed and random state values of 42 were sets to ensure reproducibility of the data generation process. These preprocessing steps enable the DL model to learn effectively from the augmented training data and produce more robust and accurate predictions.

Data Description and Structure :

- Object Detection:

Image annotation preprocessing is a crucial step in enhancing the diversity and quality of datasets for machine learning applications, particularly in the context of computer vision. The provided data outlines a comprehensive set of augmentation techniques applied during the annotation process. The annotation of the images was done manually by using RoboFlow. After that, the augmentation techniques were applied. Horizontal and vertical flips, along with 90° rotations in both clockwise and counter-clockwise directions, contribute to creating variations in object orientations. Additionally, upside-down flips introduce further complexity to the dataset. Cropping, ranging from 0% minimum zoom to 37% maximum zoom, ensures that the model encounters objects at different scales, enriching its understanding of varying perspectives. The application of noise, affecting up to 9% of pixels, simulates real-world imperfections and enhances the model's robustness. The introduction of cutout, involving the removal of portions in 5 boxes, each covering 12% of the image, serves to encourage the model to focus on relevant features while fostering generalization. Moreover, preprocessing techniques include auto-orient, applied to enhance the dataset's orientation diversity, and resizing, which stretches images to a standardized 640x640 resolution. Collectively, these preprocessing techniques contribute to a more resilient and versatile dataset, ultimately improving the performance and adaptability of the models trained on annotated images, with a specific emphasis on object detection tasks.

Data Description and Structure :

•Sensor Dataset & preprocessing:

We used a tabular dataset consist of two files for 34 days that gathered in india and record the sensor data every 15 minutes, the first dataset is the generation power and consist of 7 columns which are DATE_TIME, PLANT_ID, SOURCE_KEY ,DC_POWER, AC_POWER, DAILY_YIELD, TOTAL_YIELD, and 68778 rows. Also, the weather data related to the weather and sun data, consists of 6 columns,DATE_TIME,PLANT_ID,SOURCE_KEY, AMBIENT_TEMP, MODULE_TEMP, IRRADIATION, and 3182 rows. In the preprocessing step, we have combined the two dataset to get each module with its weather data, and dropped unnecessary columns

1. Location Dataset:

- **Dataset Overview:**
- The dataset includes comprehensive solar radiation data for various locations across Saudi Arabia.

- **Key columns include**
- Specific Photovoltaic Power Output (PVOUT specific):This is a measure of the efficiency of a photovoltaic (PV) system. It represents the amount of electrical energy (in kilowatt-hours, kWh) generated by a system per unit of peak power capacity (kilowatt-peak, kWp).

  Direct Normal Irradiation (DNI):DNI refers to the amount of solar radiation received per unit area (in kilowatt-hours per square meter, kWh/m²) by a surface that is always oriented perpendicular to the sun's rays. It measures the direct component of solar irradiance.
- Global Horizontal Irradiation (GHI): GHI is the total amount of solar radiation received per unit area (in kilowatt-hours per square meter, kWh/m²) on a horizontal surface. It includes both the direct sunlight and the diffuse sky radiation.
- Diffuse Horizontal Irradiation (DIF): Diffuse Horizontal Irradiation is the component of solar radiation received from the sky (excluding the sun's direct rays) on a horizontal surface. It's measured in kilowatt-hours per square meter (kWh/m²).

Data Description and Structure :

- Global Tilted Irradiation at Optimum Angle (GTI opta): This measures the total solar irradiance received per unit area (in kilowatt-hours per square meter, kWh/m^2) on a surface that is tilted at an optimal angle towards the sun. The optimal angle is usually determined based on geographical location and time of year.
- Optimum Tilt of PV Modules (OPTA):OPTA denotes the ideal angle and orientation for solar panels to maximize their exposure to sunlight. It is typically expressed in degrees, where the first number might indicate the tilt angle from the horizontal and the second number the compass orientation.
- Air Temperature (TEMP):This is a straightforward measurement of the temperature of the air at a specific location, typically expressed in degrees Celsius (°C).
- Terrain Elevation (ELE):Elevation refers to the height of a point on the Earth's surface above sea level, measured in meters. Terrain elevation can affect solar panel performance due to factors like atmospheric density and temperature variations with altitude.
- The data was collected by scraping the data from global solar atlas
- Dataset Characteristics:
- It consists of 27,689 entries, covering a broad range of latitudes and longitudes across the country.
- The data provides a detailed view of solar potential, including metrics like irradiance and PV output, crucial for renewable energy studies.

2. Location Preprocessing

- **Data Normalization:**
- The dataset undergoes normalization to standardize the solar radiation scores and other related metrics.
- This step is essential to ensure comparability and accuracy in subsequent analysis and modeling.
- Identifying Optimal Locations:
- The preprocessing includes techniques to identify the best locations for solar energy projects, considering factors like irradiance, temperature, and geographical positioning.

Methodology Proposed Techniques

Image Classification

Transfer Learning (TL) is a technique in DL that uses pre-trained models such as MobileNet, to improve the performance of new models for specific tasks. Utilizing the knowledge of a pre-trained model, TL can considerably decrease the time and computational resources necessary for new tasks, particularly when the training data is restricted. Moreover, in image classification, TL involves fine-tuning the pre-trained model by removing the final classification layer and adding a new layer explicitly trained for the new task.

- MobileNet

MobileNet is a widely recognized and influential CNN architecture that has revolutionized the field of DL for mobile and embedded devices. MobileNet was proposed by Andrew G. Howard et al., it addresses the challenge of deploying powerful computer vision models on resource-constrained platforms. It specifically tackles the challenge of deploying DNN on resource-constrained devices like mobile phones and embedded systems. The key innovation of MobileNet lies in its utilization of depthwise separable convolutions, which splits the convolution into depthwise and pointwise convolutions. The former applies a single filter to each input channel individually to capture spatial information, while the latter combines the outputs of the depthwise convolution using 1x1 convolutions to mix features across channels. By decoupling spatial and channel-wise filtering, MobileNet significantly reduces computational complexity and model size without sacrificing accuracy. Additionally, MobileNet introduces the width multiplier hyperparameter, enabling scaling of channel numbers in each layer to optimize the model's size and accuracy trade-off based on specific deployment requirements.

Methodology Proposed Techniques

Object Detection

- YOLOv8

YOLOv8, the eighth iteration of the You Only Look Once (YOLO) object detection algorithm, continues the legacy of its predecessors in revolutionizing real-time computer vision tasks. Known for its efficiency and speed, YOLOv8 employs a convolutional neural network architecture to process images in a single pass, swiftly predicting bounding box coordinates and class probabilities for detected objects. The advancements introduced in YOLOv8 are geared towards improving accuracy and speed, making it a versatile solution for applications requiring rapid and precise object detection, such as in autonomous vehicles, surveillance systems, and robotics. Open source in nature, YOLOv8 provides a platform for researchers and developers to access and modify its codebase, facilitating customization for specific tasks. Its class-agnostic nature enables simultaneous detection and classification of multiple object classes, and its training procedure involves optimizing parameters based on annotated datasets. YOLOv8 exemplifies the ongoing efforts to push the boundaries of real-time object detection, contributing to the evolving landscape of computer vision.

Methodology Proposed Techniques

Regression

- Ridge algorithm:

Ridge regression is a linear regression algorithm designed to address the challenges of multicollinearity and overfitting in predictive modeling. In traditional linear regression, where the goal is to minimize the sum of squared differences between predicted and observed values, multicollinearity among features can lead to unstable and inflated coefficient estimates. Ridge regression introduces a regularization term, proportional to the square of the coefficients, to the objective function. This regularization term, controlled by a hyperparameter called alpha, discourages the model from relying too heavily on any particular features and mitigates the impact of multicollinearity. By penalizing large coefficient values, ridge regression encourages a simpler model that generalizes well to new, unseen data. The regularization strength, determined by the alpha parameter, allows users to fine-tune the balance between fitting the training data closely and preventing overfitting. Ridge regression is a valuable tool in scenarios where datasets exhibit correlated features, offering a robust solution for linear regression tasks in the presence of collinearity.

Methodology Proposed Techniques

Recommendation System

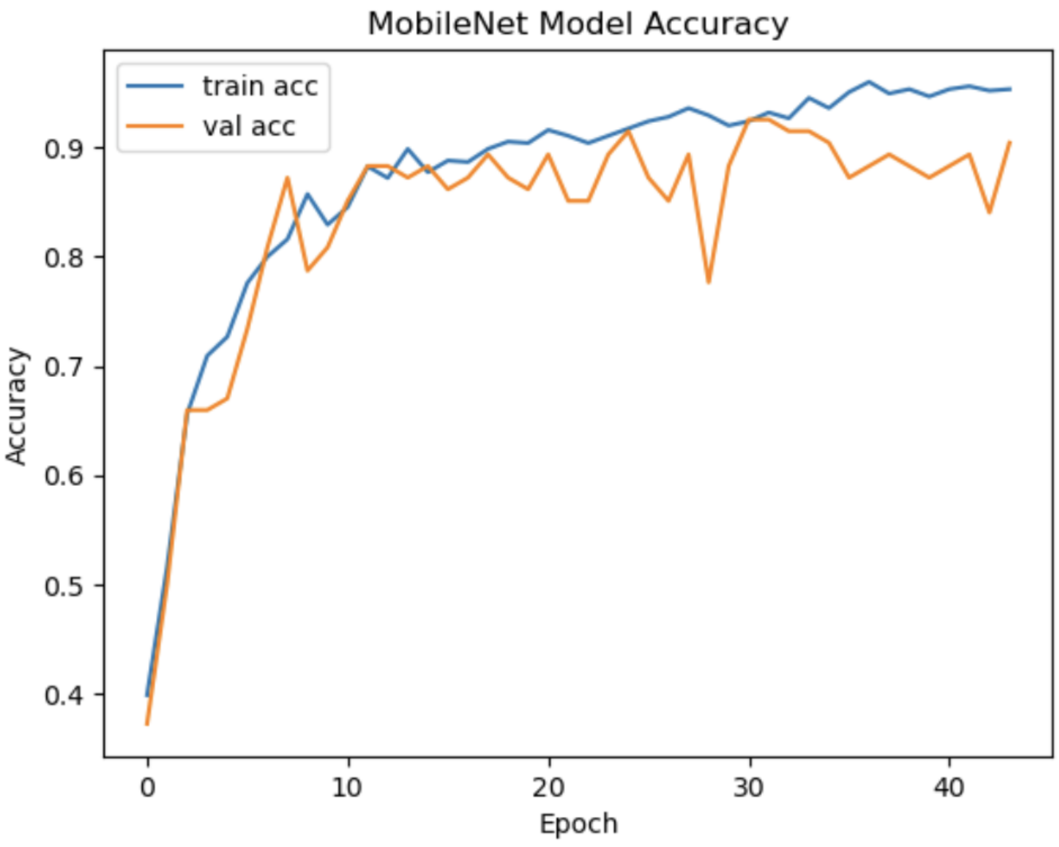
- Algorithms :

•**Analysis Approach:**
We've used algorithms tailored to analyze solar atlas data, particularly focusing on location-based analysis.
•These include the k-means unsupervised classification algorithm. The optimal number of clusters was obtained using the elbow method.
•The latitude and longitude coordinates were converted to explicit geographic python objects using Shapely and Geopandas. This ensures efficiency and avoids redundancy.

•**Application in Recommender System:**
•The algorithms are likely used to recommend optimal locations for solar energy installations, factoring in environmental and logistical parameters.
•This forms a crucial part of a recommender system aimed at aiding decision-making in renewable energy projects.
•In recommender system, when a new latitude or longitude is selected, the location that has similar solar data, is provided.

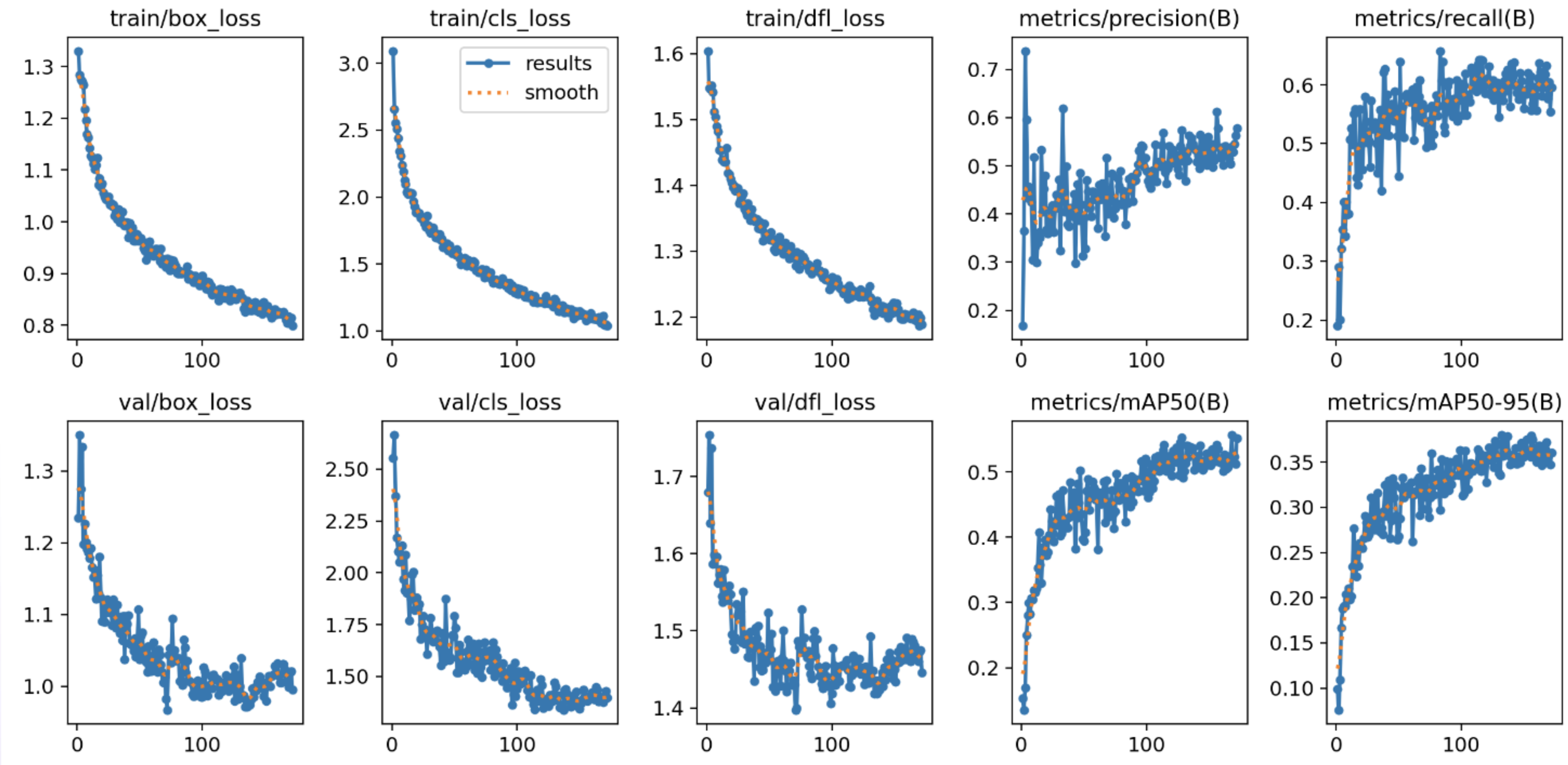
Discussion and Results:

For the image classification we have train the mobileNet model for 100 epochs with 64 batch size, and gained 91% accuracy, and 0.39 loss. See below images.



MobileNet	Accuracy	Loss
Training	0.9507	0.1334
Validation	0.8617	0.6153
Testing	0.9166	0.3935

Also. For object detection we trained our data with yolov8, using more than 150 epochs, and gained acuracy with 54.1%, precision 52.7%, and recall 58.2%.



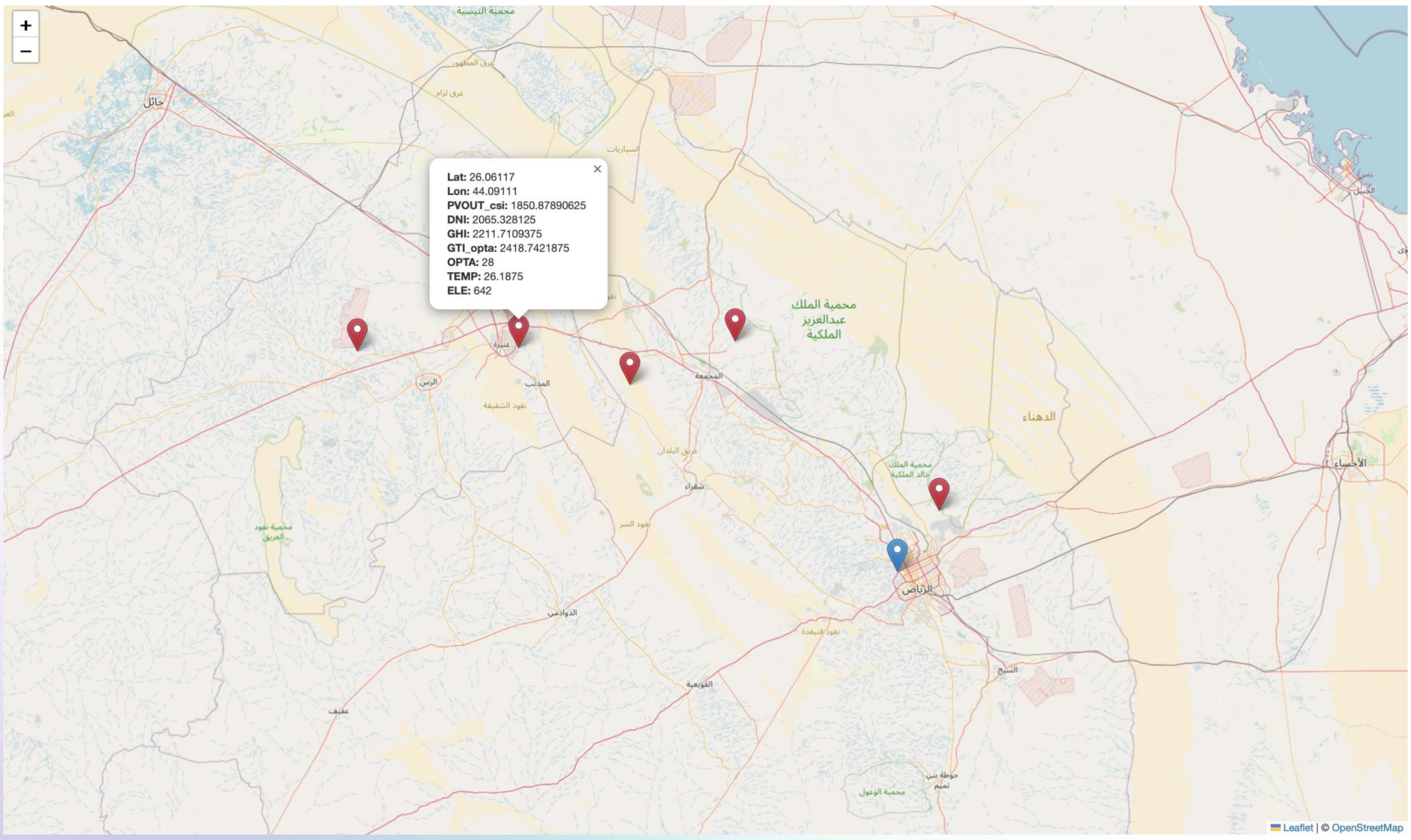
Discussion and Results:

In the Ridge Regression model, we trained the model using training dataset Split that consist of 54034 records and test it on testing dataset split with 14740 records gained 99% R2 Score, 1.08 MSE, 0.67 MAE, and 1.04 RMAE.

```
training result:
================================
Mean Absolute Error (MAE) - Training: 0.6617800209579783
Mean Square Error (MSE) - Training: 1.108541845837631
Root Mean Squared Error (RMSE) - Training: 1.052873138529819
R2 - Training: 99.99931719474046
```

```
testing result:
================================
Mean Absolute Error (MAE): 0.6786291171179187
Mean Square Error (MAE): 1.0886896333795666
Root Mean Squared Error (RMSE): 1.0434029103752618
R2- Testing:  99.99915655149726
```

Our recommendation system recommends similar location based on the location choose on the map, and provide all required information related to each location, such as, latitude, longitude, DNI, DIF, GHI, temperature, and PVOUT. In the below figures, in the left figure or map, the user choose his preferred location, and the recommended locations will be shown on the right figure.



Conclusion and Future Work

In conclusion, this capstone project has presented a comprehensive and innovative approach to enhancing the efficiency and reliability of solar panel installations through a combination of deep learning and traditional machine learning techniques. The utilization of a MobileNet pre-trained model for predicting the failure status of solar panels demonstrates the potential of leveraging state-of-the-art image classification methods in the renewable energy sector. The integration of YOLO8 for object detection in solar panels further contributes to the robust monitoring and maintenance of solar installations. Additionally, the application of a Ridge regression model to predict energy generation based on sensor data introduces a data-driven methodology for optimizing energy output and resource utilization. Lastly, the incorporation of a recommendation system for identifying optimal locations for solar installations in Saudi Arabia underscores the significance of strategic planning for renewable energy deployment. The synergy of these methodologies presents a holistic approach to addressing challenges in the solar energy domain, promoting sustainability, and fostering advancements in renewable energy technologies and meet our Saudi vision of 2030. This project provides valuable insights that can guide future endeavors aimed at enhancing the performance and longevity of solar energy systems, ultimately contributing to a more sustainable and environmentally conscious energy landscape.

For our future work, we aimed to enhance all of our deep learning, and machine learning model and use a local Saudi data, then integrate it along with intelligent robots that automatically detection and maintenance, without any human intervention.

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