A FRAMEWORK FOR USING SATELLITE IMAGES TO ESTIMATE PV SYSTEMS' GENERATING CAPACITIES

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***Abstract*— Numerous initiatives to rely on new renewable energy sources, such solar electricity, have been sparked by the increased interest in global warming. With an increase in home photovoltaic (PV) panels that are available to the public, more precise calculations of energy generation are now possible. Segmenting satellite images offers a straightforward and inexpensive way to categorize solar panels..This work suggests a method for classifying and segmenting solar panels that combines the watershed algorithm with deep learning approaches. First, a Convolutional Neural Network (CNN) architecture with the ResNet, EfficientNet, and Inception architectures is used for classification. Through the fine-tuning of pre-trained networks on a heterogeneous dataset of solar panels, transfer learning improves performance. The categorization model recognizes solar panels in a variety of settings with accuracy, making maintenance and monitoring easier. After classification, the watershed method uses intensity gradients to precisely delineate solar panels from the background. Tasks like defect detection and layout optimization are made easier when deep learning-based classification and watershed segmentation are combined. The outcomes of the experiments show how well the suggested method performs in terms of segmenting and classifying solar panels under various circumstances. A flexible automated solar panel management solution is provided by the combination of deep learning and the watershed algorithm, which promotes increased sustainability and efficiency in solar energy systems.**

***Keywords*— renewable energy; photovoltaic (PV); Satellite image; segmenation; watershed method; deep learing**

I. INTRODUCTION

In the current era, the spotlight on sustainability and renewable energy sources has led to a surge in the utilization of solar panels, marking a significant stride towards a more eco-friendly future. Solar energy, drawn from the boundless radiance of the sun, emerges as a pivotal solution in combatting climate change while diminishing reliance on finite fossil fuels. This surge in solar panel adoption owes much to advancements in technology, heightened environmental consciousness, and compelling economic incentives. Advancements in solar panel technology have revolutionized the renewable energy landscape, rendering solar power more accessible and efficient than ever before. Breakthroughs in photovoltaic cell design, battery storage systems, and manufacturing techniques have notably enhanced the efficacy and affordability of solar panels, rendering them a feasible choice for residential as well as commercial applications. Additionally, the modular nature of solar panel setups allows for scalability, permitting users to tailor systems according to their energy requirements and available space. Nevertheless, despite the remarkable strides made in solar technology, the initial costs associated with solar panel installations remain a significant consideration for potential adopters. Estimating the capacity and cost of solar panel systems conventionally involves intricate calculations and evaluations, often necessitating specialized expertise and knowledge. Factors such as geographical location, solar irradiance, shading, and system configuration all exert considerable influence on determining the optimal size and output of a solar installation. Traditional methods of estimating solar panel capacity typically entail utilizing solar irradiance data, conducting site surveys, and undertaking engineering analyses to evaluate the solar potential of a particular location. This process demands meticulous planning and assessment to ensure optimum performance and cost-effectiveness. Furthermore, the financial aspects of solar installations, encompassing incentives, rebates, and financing options, must be carefully evaluated to gauge the overall return on investment. In this regard, the proliferation of online solar calculators and software tools has streamlined the process of estimating solar panel capacity and costs for consumers and businesses alike. These tools harness geographic data, system specifications, and energy consumption patterns to generate precise projections of solar energy production and financial returns. By empowering users to assess the feasibility and economic viability of solar investments more efficiently, these tools are propelling further adoption of solar energy across diverse markets. In conclusion, the escalating deployment of solar panels heralds a seismic shift in the global energy panorama, presenting a sustainable alternative to conventional power sources. While upfront costs and capacity estimations have historically posed formidable barriers to adoption, technological advancements and the availability of sophisticated analysis tools are rendering solar energy more accessible and economically feasible than ever before. As societies continue to prioritize environmental preservation and energy autonomy, solar power emerges as a cornerstone in sculpting a cleaner, brighter future for generations to come.

II. RELATED WORK

With greater accuracy and recall than 90% in recollections, the writers identified and calculated the dimensions of solar PV installations.With a recall rate of more than 90%, the authors accurately located and calculated the dimensions of solar PV systems in both residential and non-residential settings. Yuan et al. also employed a CNN to map solar panels on a broad scale using high-resolution aerial photos (Yuan et al.,2016). They put forth a network architecture that records semantic information at several levels and allows for prediction at the pixel level. By employing this method, the writers were able to attain 0.873 completeness, 0.855 correctness (San Francisco), 0.84 completeness, and 0.812 correctness (Boston). Solar-Net was created by Hou et al. to locate and map solar PV systems across China.

III PROPOSED SYSTEM

The goal of the ongoing effort is to automatically identify solar PV systems and their potential energy output in a particular geographic area using a novel artificial intelligence approach. In order to forecast power based on a particular satellite image, the ensemble model combining (resent, Inception, efficient net) was trained on the high resolution satellite photos of PV panels that were collected from the Kaggle website.

3.1 Data Collection:

There aren't many publicly accessible datasets for the classification of satellite photos of solar power panels in different regions. The dataset is divided into five groups according to different types of solar power panel configurations and satellite photographs of the sun. We use labels for power generation and photos of solar panels as features.

3.2 Pre-Processing:

Pre-processing is a technique used to improve image quality and boost visualization. Image processing is an important step in the solar panel dataset that helps to enhance the image quality. This may be one of the most important elements in getting accurate and good outcomes in the next stages of the suggested process. Images of solar panels may have several problems that cause the image to be poorly visualized. Inadequate or low-quality photos could produce disappointing outcomes. We carried out backdrop removal, removing unnecessary blood supplies, image improvement, and noise removal during the preprocessing stage.

3.3 Train-Test Split and Model Fitting:

We now separate the training and testing data in our dataset. The purpose of this split is to evaluate our model's performance on unknown data and ascertain the extent to which our model has generalized on training data. A model fitting, which is a crucial stage in the model-building process, comes next.

3.4 Model Evaluation and Predictions:

This last stage evaluates the model's performance on testing data using a variety of scoring measures; I have chosen to use the 'accuracy score' to do this. The process begins with the creation of a model instance. Next, the training data is fitted to the model using the fit method. Finally, predictions are made on the testing data, or x_test, using the predict method. The predictions are then saved in a variable named y_test_hat. The y_test and y_test_hat will be fed into the accuracy_score function for model assessment, and the results will be stored in a variable named test_accuracy, which will hold the testing accuracy of our model. For a range of classification algorithm models, we performed these procedures and obtained corresponding test accuracy score.

3.5 Flask webapp:

we develop a webapp using flask framework and mysql database. User can register login, upload solar satellite image and under view images click predict to get power generation of solar panels at that location.

3.6 Algorithms:

3.6.1 CNN Architecture Process & Inputs:

CNNs use a variety of layers to convert an image into output that the model can comprehend. Convolutional layer: applies a filter that scans the image many pixels at a time to build a feature map.

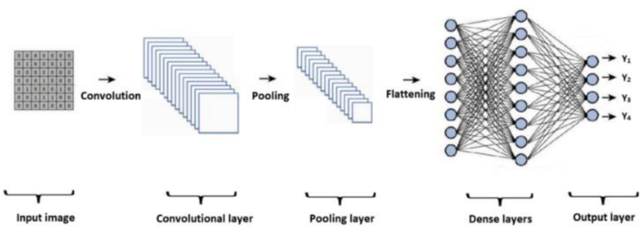

Fig no:3.6.1

In order to efficiently store the information produced by the convolutional layer, the pooling layer reduces its size. The outputs are flattened into a single vector by the fully connected input layer.Applying weights to the inputs produced by the feature analysis is the fully connected layer. The output layer that is fully connected produces the final probabilities needed to identify the image class.

3.6.1.1 Process:

All of the network's training samples are iterated through both forward and backward propagation until the ideal weights are found and only the strongest and most predictive neurons are turned on to provide predictions.Every time it trains, the model goes through several epochs, going through all of the training samples once forward and once backward.

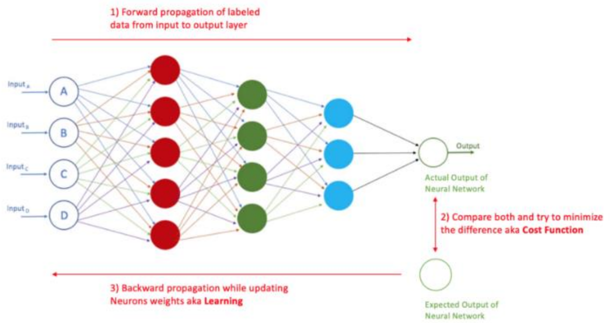

Fig no:3.6.1.1

Forward propagation compares the difference between the actual and expected target for each tagged image, computing the loss and cost functions. Gradient descent is a technique used in backward propagation to update the weights and bias of individual neurons, giving greater weight to the neurons with the highest predictive power until it reaches the ideal combination of activations. The loss measure decreases when the model learns to anticipate the target more accurately as it encounters more examples. The average loss over all samples, which indicates overall performance, is taken by the cost function.

3.6.1.2 Inputs:

The inputs for the model must always be in a 4D array with the dimensions of (batch_size, height, width, depth). The quantity of training samples in a single epoch is known as the batch size; the larger the batch size, the more memory you will require. Length & Breadth: The image's pixel dimensionsDepth: Black & White (1), Red, Green, or Blue (3)

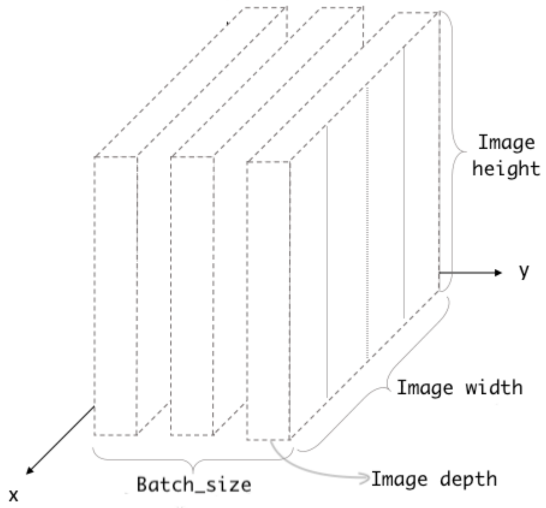

Fig no:3.6.1.2

3.7 System Architecture:

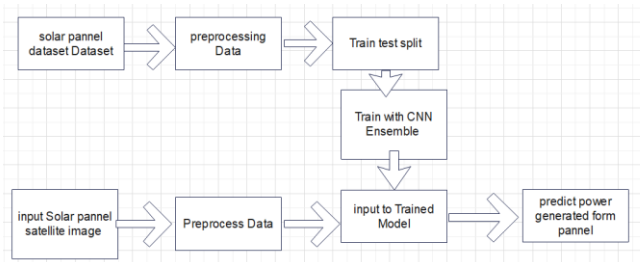

Fig no: 3.7

After being processed and turned into processing data, the solar panel dataset is transformed into a train test split.It is currently being processed or trained using CNN ensemble.On the other hand, as illustrated in Figure No. 3.7, the input solar panel image is preprocessed before being fed into the trained model, which yields the predicted value.

IV RESULTS

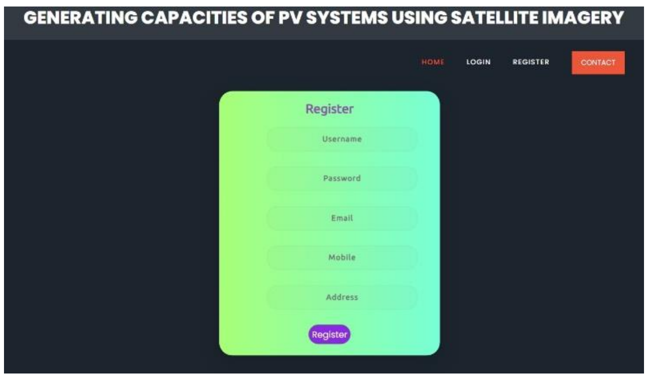

Fig no: 4.1

The figure no: 4.1 demonstrates the system's interface where registration is required for the next step.

Fig no: 4.2

The login page is used to specify the particular person's data, and this is the interface of that page, as shown in Fig no: 4.2

Fig no: 4.3

There is an interface for the solar panel satellite image to get power generation from it as shown in fig no: 4.3

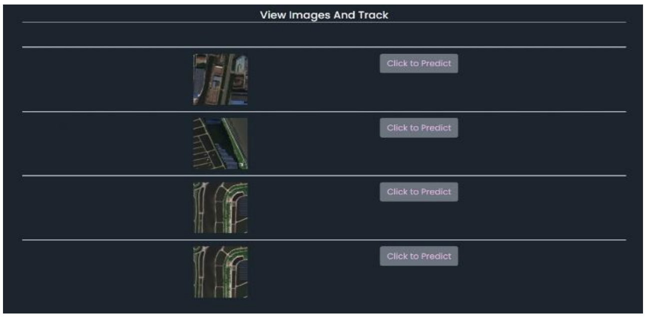

Fig no: 4.4

This is the uploaded image as shown in fig no: 4.4

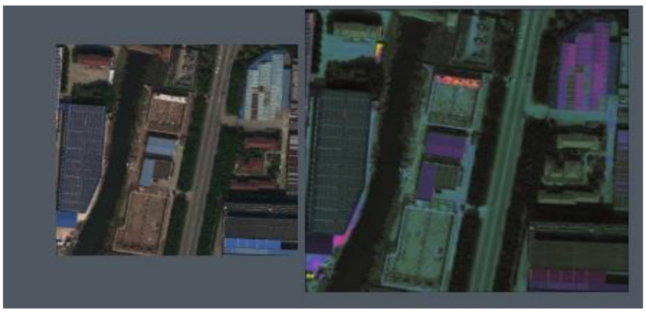

Fig no: 4.5

The fig no: 4.5 shows the image of the uploaded image and the processed image.

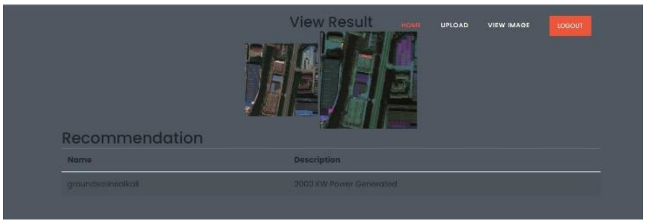

Fig no: 4.6

The value of the PV system generated is shown in Fig no: 4.6

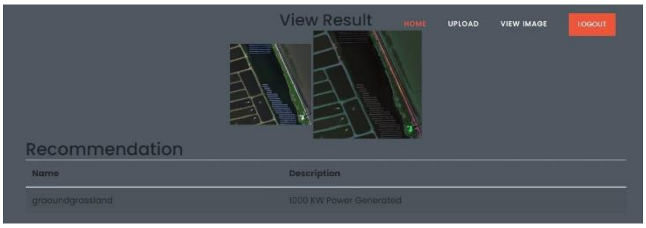

Fig no: 4.7

The value of the PV system generated is shown in Fig no: 4.7

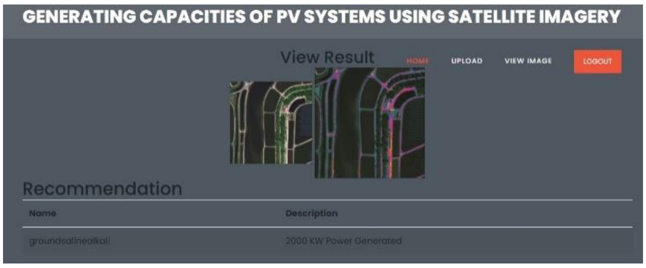

Fig no: 4.8

The value of the PV system generated is shown in Fig no: 4.8

V MODEL EVALUATION

5.1 Accuracy:

A comparison of the validation and taining accuracy is shown in Figure 5.1. illustrating the variation between then and now. While the x axis displays the epoch, the y axis displays accuracy.

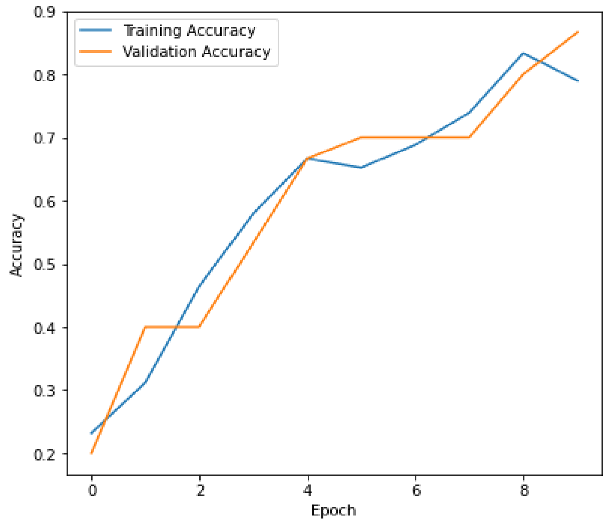

Fig no: 5.1

VI CONCLUSION

Despite rising raw material prices, solar PV manufacturing is growing significantly and is now a major energy component in many countries. Massive installations of solar PV systems in homes and businesses, however, are posing new difficulties for a variety of stakeholders, including network and market operators. Central databases for distributed solar PV may be inaccurate or out-of-date, and rooftop solar PV systems' precise locations and capacities are sometimes not recorded. The use of satellite and aerial images to automatically determine the positions and capabilities of solar PV systems over wide areas is therefore becoming more and more popular. With CNN as the backbone, this study presents a method for evaluating the technical potential energy generating output utilizing the CNN Ensemble model (resent, efficient net, inception). The findings demonstrate that the CNN-based Ensemble approaches are capable of accurately estimating solar energy generation by exactly calculating the area of photovoltaic panels using satellite photos. The results imply that this strategy could work with more development.

VII FUTURE SCOPE:

On the basis of such shortcomings, some suggestions are proposed and discussed, which are believed to achieve good results in the future. We can use RCNN algorithm to segment position defect solar panels and show result..

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