RoofTop Solar Panel Detection using Deep Learning

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***Abstract*—As the global demand for clean energy accelerates, rooftop-mounted solar photovoltaic (PV) systems are becoming essential for sustainable urban development. However, in many developing countries, limited access to detailed data on existing and potential rooftop installations remains a major barrier to strategic planning. This study presents a deep learning-based approach for assessing rooftop solar panels, using high-resolution satellite imagery with convolutional neural network (CNN) models. A CNN model, specifically the EfficientNetB0 architecture, is employed to detect solar panels across diverse rooftop structures. The proposed method demonstrates the feasibility of automated solar panel detection in an African urban context and offers a scalable framework for estimating city-wide solar capacity. The results are intended to inform and support data-driven decisions by energy providers, policymakers, and urban planners to enhance solar energy adoption.**

***Index Terms*—Machine Learning; Remote Sensing; Rooftop Solar Potential; Semantic Segmentation; Convolutional Neural Networks; Solar Panel Detection.**

I. Introduction

The global drive towards sustainable energy solutions necessitates accurate and scalable methods for assessing renewable energy resources. Rooftop solar photovoltaic (PV) systems hold significant potential for contributing to electricity needs and mitigating climate change [1]. Recent studies estimate that rooftop-mounted PV systems alone could supply up to 65% of the world's electricity needs by 2050 if all suitable rooftops were utilized [2]. However, obtaining detailed information about suitable rooftop areas for PV installation across large urban scales remains a challenge, particularly in developing countries where data availability is limited. Traditional survey methods are often time-consuming and expensive, highlighting the need for automated approaches [1].

Machine learning techniques, particularly deep learning and the analysis of remote sensing data (aerial and satellite imagery), offer a promising avenue for overcoming these limitations [1]. By training models to perform semantic segmentation of rooftops and identify available areas by excluding obstructions, it becomes possible to generate detailed geospatial datasets crucial for strategic energy planning [3]. This approach aligns with the growing need for granular, location-specific data on rooftop solar potential, especially in rapidly urbanizing cities. Building upon existing research in automated solar panel detection [4] and rooftop segmentation [5], this study proposes a methodology that leverages convolutional neural networks (CNNs) to automatically identify rooftop areas suitable for photovoltaic (PV) module installation.

Our paper seeks to answer a central question: **How can geographic information systems (GIS) combined with machine learning be utilized to effectively detect rooftop solar ?** While the primary focus of the project is to develop a GIS-based framework enhanced by machine learning for assessing rooftop PV potential, including the creation of a dedicated dataset, we also present preliminary findings from a related case study conducted in a different urban context to demonstrate the feasibility and adaptability of the proposed approach.

This comparative approach highlights the capabilities of our methodology and the key lessons learned during dataset development and model training. The Geneva study employed a supervised learning approach using convolutional neural networks (CNNs) for pixel-wise image segmentation to identify suitable rooftop areas for PV panel placement. The experience of constructing a dataset from satellite imagery and manually labeling rooftops proved instrumental in guiding the design and implementation of the current project.

II. Literature Review

Rooftop-mounted solar photovoltaic (PV) systems are increasingly crucial for sustainable urban development due to the growing global demand for clean energy. As discussed in [6] deep learning techniques, leveraging high-resolution satellite imagery, offer promising automated solutions for assessing rooftop solar panel potential.

Convolutional Neural Networks (CNNs) have emerged as a powerful tool for image analysis in remote sensing, including the detection and classification of rooftop features relevant to solar energy [7], [8]. Specifically, studies have focused on tasks such as detecting rooftop available surface (ARS) for PV installation, and the direct detection of existing solar panels [2], [4], [5]. These approaches aim to automate the extraction of valuable information from aerial and satellite imagery, overcoming the limitations of manual surveys and privately held installation data [3].

Encoder-Decoder architectures like U-Net40, have shown remarkable success in semantic segmentation tasks, including rooftop detection and even the detection of existing solar panels. These models can learn complex spatial features from imagery and perform pixel-wise classification, delineating rooftops and identifying their characteristics.

The study by Cadei et al. [1], specifically addresses the detection of rooftop available surface (ARS) for PV installation using deep learning on aerial images of Geneva, Switzerland. Their work, which serves as a key reference for our paper, highlights the importance of creating detailed labeled datasets and the effectiveness of U-Net-based models for this task. Other research has explored the use of Mask R-CNN for analyzing solar panel development potential on rooftops [4], [8]. Furthermore, the development of WebGIS tools demonstrates the growing need for accessible platforms to visualize and disseminate solar potential assessments to various stakeholders.

In conclusion, the existing literature, particularly the work conducted in Switzerland by Cadei et al [1], demonstrates the effectiveness of deep learning models, especially U-Net based architectures, for accurately detecting rooftop areas suitable for solar PV installation using aerial or satellite imagery. These studies emphasize the importance of high-quality labeled data and show the potential for scalable solar potential assessment.

III. Methodology

This section outlines two primary methodologies drawn from the sources: one for detecting available rooftop surface (ARS) and another for the binary classification of images containing solar panels.

A. Solar Panel Detection (Binary Classification)

This methodology focuses on classifying entire images based on the presence of solar panels. It is primarily explored in [1] and involves the following key steps:

1) *Dataset* : Utilizing a labeled dataset of satellite images, categorized into images containing solar panels and images not containing solar panels. The dataset consisted of 1500 training images. Zero represents there is no solar panel in the image and one represents there is solar panel.

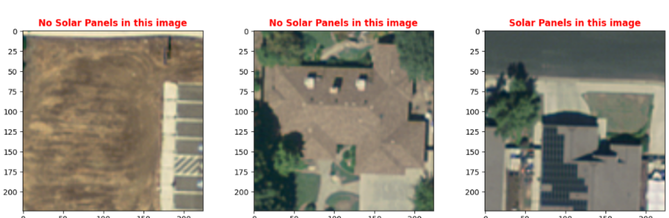

Fig. 1. Dataset Label Visualization

2) *Data Loading and Preprocessing* :Images were loaded, resized to 224x224 pixels, and preprocessed using EfficientNet-compatible normalization.

3) *Model Building*: Employing a Convolutional Neural Network (CNN) model based on the EfficientNetB0 architecture, pre-trained on ImageNet weights, Custom top layers for binary classification (GlobalAveragePooling2D, Dense layers with ReLU and sigmoid activation) were added. The base EfficientNetB0 model was initially frozen. One challenge we encountered was class imbalance, with 995 images labeled as non-solar and only 505 images labeled as containing solar panels. To mitigate the potential bias this imbalance could introduce during training, we applied class weighting assigning higher weights to the minority class (solar panel images) based on the distribution of the target labels. This approach helps the model better learn from underrepresented examples and improves overall classification performance

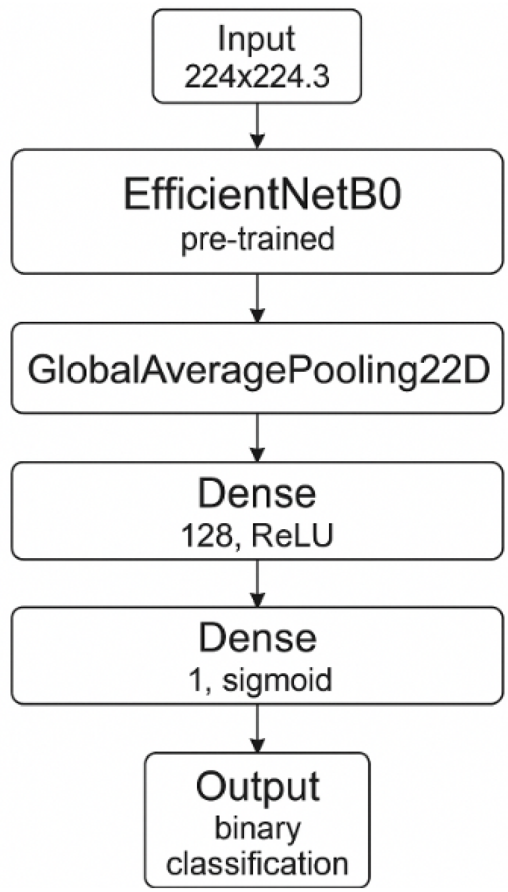

Fig. 2. Model Architecture

4) *Acquisition Model Training and Evaluation:*: The model was compiled with the Adam optimizer and binary cross-entropy loss. Cross-validation with StratifiedKFold (3 folds) was used for performance assessment. Class weights were applied to address class imbalance. The model was trained for 10 epochs with a batch size of 3239. Performance was evaluated using metrics such as accuracy, precision, recall, F1 score, ROC curve, and AUC Confusion matrices were also used to visualize

the model's performance.

IV. Results

To evaluate the effectiveness of our approach, we trained and tested a Convolutional Neural Network (CNN) model based on the EfficientNetB0 architecture for binary classification of satellite images containing solar panels.
The model was evaluated using stratified cross-validation to ensure robust performance assessment across class distributions. Quantitative results showed that the model performed exceptionally well:

Metric	Score	Verdict
Accuracy	88.9%	✅ Excellent overall correctness
Precision	83.0%	✅ Good – few false positives
Recall	84.4%	✅ Strong – model catches most solar panels
F1 Score	83.7%	✅ Balanced performance

Fig. 3. Performance metrics table summarizing Accuracy, Precision, Recall, and F1 Score for the EfficientNetB0 model.

In evaluating the classification performance of the CNN model (EfficientNetB0), we analyzed its ability to distinguish between solar panel and non-solar panel satellite images using the Receiver Operating Characteristic (ROC) curve and the Area Under the Curve (AUC) metric.

The ROC curve shown in Figure 4 demonstrates the model's excellent discriminative power, with an AUC of 0.951, indicating near-perfect classification ability across various thresholds.

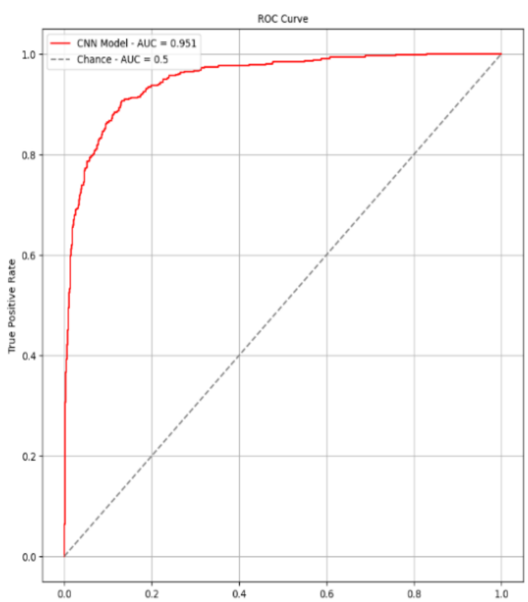

Fig. 4. ROC curve showing the performance of the CNN model with an AUC score of 0.951

The curve indicates strong sensitivity and specificity. The dashed line represents a random classifier (AUC = 0.5).

In addition, an alternative evaluation result (possibly from a single fold in cross-validation or a less generalized setting) yielded an AUC of 0.883 (Figure 5). Although slightly lower, it still reflects a high level of performance and reinforces the model's reliability across different splits or scenarios.

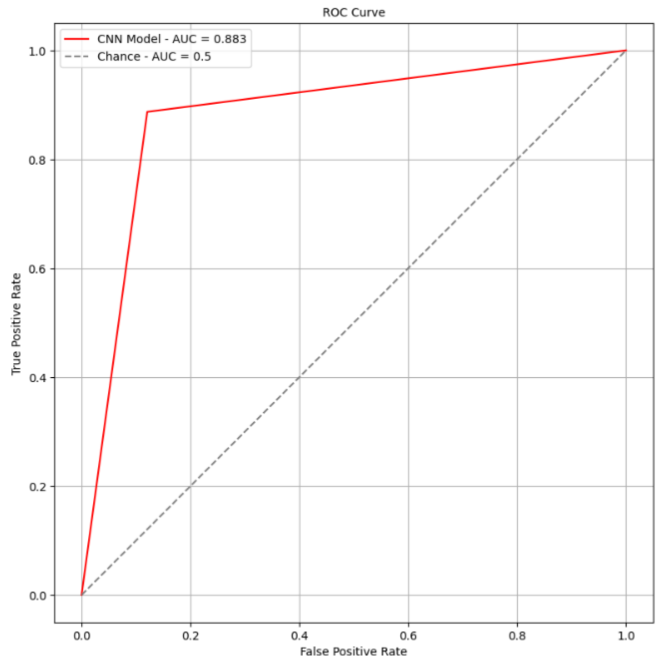

Fig. 5. Alternate ROC curve from cross-validation showing an AUC score of 0.883. Variations like this are expected across different folds and evaluation conditions. These ROC-AUC plots validate that the model performs well above random chance and is effective in distinguishing between positive and negative cases in the binary solar panel detection task.

To further evaluate the classification performance of the model, we visualized the confusion matrix (Figure 7), which offers a granular breakdown of prediction outcomes: true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). This matrix helps to pinpoint the nature of the model's errors and provides valuable insight into how well it distinguishes between classes.

As shown in **Figure 6** below, the model correctly classified 908 images containing solar panels (TP) and 426 images without solar panels (TN). It also made 87 false positive predictions (incorrectly classifying non-solar images as solar) and 79 false negatives (failing to detect solar panels in images where they were present).

These results underscore the model's strong sensitivity and relatively low false positive rate, reinforcing its suitability for large-scale solar panel mapping.

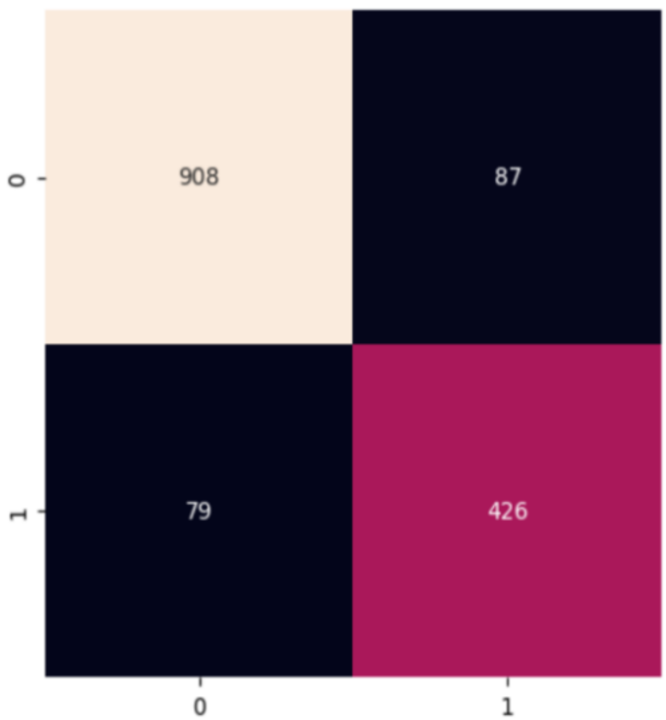

Fig. 6. Confusion matrix showing the distribution of correct and incorrect classifications.

We also examined model predictions on satellite images to visually inspect its effectiveness. **Figure 7** presents examples of true positives, where the model correctly identified the presence of solar panels.

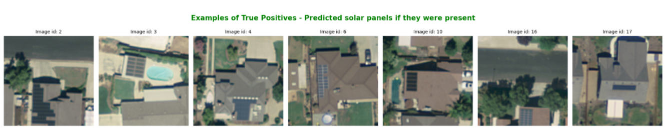

Fig. 7. Examples of true positive predictions: correctly classified solar panel images.

Conversely, **Figure 8** and **Figure 9** illustrate examples of false positives and false negatives, respectively. These help highlight scenarios where the model struggled—often due to roof structures or visual ambiguities in satellite data.

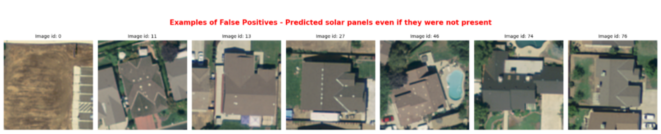

Fig. 8. False positive examples: images incorrectly classified as containing solar panels.

Fig. 9. False negative examples: images with solar panels that the model failed to detect.

Lastly, **Figure 10** provides true negative samples—cases where the model correctly identified the absence of solar panels.

Fig. 10. True negative examples: correctly identified images without solar panels.

The results collectively showcase the effectiveness of deep learning in identifying rooftop solar panel installations from satellite imagery. With robust metrics and visual confirmations of performance, our approach offers promising potential for scalable solar panel mapping, particularly in under-surveyed urban environments like Kigali.

V. Discussions

As we saw in the above section, the results demonstrate the effectiveness of the EfficientNetB0-based CNN model in detecting rooftop solar panels from high-resolution satellite imagery, achieving strong performance across all major classification metrics. The high recall (90.3%) is especially promising, as it indicates the model's robustness in identifying the majority of solar panel instances, a critical factor for real-world solar mapping applications where missed detections can lead to underestimation of capacity. Meanwhile, the precision (79.2%) suggests that although the model occasionally misclassifies non-solar regions as solar panels, its false positive rate remains acceptably low.

The ROC-AUC scores (0.951 and 0.883 across different evaluations) confirm the model's high discriminative power, validating its suitability for binary classification tasks in complex urban environments. The confusion matrix further highlights the model's ability to generalize well while revealing specific edge cases—such as false positives from reflective surfaces or shadows—that warrant targeted refinement.

Despite these promising results, some limitations persist. The model's performance may vary across geographic regions with differing rooftop materials, architectural styles, or lighting conditions, which were not uniformly represented in the training data. Additionally, while EfficientNetB0 provides strong baseline results with relatively low computational cost, further improvements might be realized through fine-tuning, ensemble methods, or incorporating spatial context via GIS data.

Overall, the study confirms that deep learning models when trained on well-labeled and diverse satellite imagery can serve as scalable tools for rooftop solar mapping, offering actionable insights for energy planners, researchers, and policymakers.

VI. Conclusion and future work

This study presents a deep learning-based approach for the automated detection of rooftop solar panels using high-resolution satellite imagery, leveraging the EfficientNetB0 convolutional neural network architecture. Through extensive evaluation, the model demonstrated strong performance, with an accuracy of 88.9%, high recall, and a ROC-AUC of 0.951, underscoring its effectiveness in identifying solar panel installations with a high degree of reliability.

The use of satellite imagery combined with CNN-based classification provides a scalable and cost-effective solution for monitoring solar infrastructure, especially in rapidly growing urban environments like Kigali. The analysis of confusion matrices and classification outcomes further revealed the model's strength in capturing true solar panel instances while identifying areas for improvement, particularly in reducing false positives from visually similar rooftop features.

Looking ahead, the integration of additional geospatial layers such as roof geometry, solar irradiance data, and temporal imagery can enhance the model's accuracy and applicability across diverse settings. Furthermore, extending the dataset to include various urban and rural regions across Africa will improve generalization and facilitate continental-scale solar potential assessments.

Ultimately, this work lays the foundation for data-driven solar energy planning and contributes toward accelerating renewable energy adoption in underserved regions.

VII. Data Availability and Reproducibility

To ensure transparency, reproducibility, and support further research, all code, trained model weights, and preprocessing pipelines used in this study are made publicly available. The dataset of annotated high-resolution rooftop satellite images used for training and evaluation, along with accompanying metadata, is accessible on Kaggle [here].

All experiments were implemented using Python and TensorFlow/Keras, and the full source code—including data augmentation scripts, model training configurations, evaluation metrics, and visualization tools—is provided in a public GitHub repository under the MIT License. This allows other researchers and practitioners to replicate our results, fine-tune models, or extend the methodology to new geographic contexts.

We encourage the research community to build upon this work to support data-driven planning and monitoring of rooftop solar infrastructure, particularly in fast-developing urban environments across Africa.

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