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# Optimization of solar panel installation potential mapping based on convolutional neural network



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## Abstract

*The increasing global energy demand and the depletion of fossil fuel resources have accelerated the transition toward renewable energy. Solar energy is considered one of the most promising sustainable energy sources. However, identifying suitable locations for solar panel installation remains challenging due to geographic and environmental variability across different regions. This study proposes a Convolutional Neural Network (CNN)-based approach to map potential solar panel installation areas using high-resolution satellite imagery. The model is designed to extract spatial features from land surfaces, including land cover characteristics, building density, and reflectance patterns derived from Sentinel-2 imagery obtained through Google Earth Engine. The proposed framework utilizes a VGG19-based architecture with transfer learning to improve feature extraction and classification performance. Experimental results demonstrate that the proposed model achieves an accuracy of 94.2% in classifying areas suitable for solar panel installation. These findings indicate that deep learning–based spatial analysis can provide an effective approach to support large-scale solar energy planning and decision-making.*

## 1. Introduction

The growing demand for sustainable and renewable energy sources has accelerated global interest in solar energy as a primary alternative to fossil fuels [1]-[2]. Solar power, being abundant and environmentally friendly, offers significant potential for energy diversification, especially in tropical regions such as Indonesia [3]. However, identifying suitable locations for large-scale solar panel installations remains a critical challenge, particularly in archipelagic countries where geographic and environmental conditions vary substantially [4]. Conventional approaches to solar energy potential mapping often rely on numerical environmental parameters such as solar radiation, temperature, and topography, which, while informative, lack the spatial and visual context necessary for precise land suitability analysis [5]-[8]. In many solar energy studies, potential mapping is typically formulated as a regression or quantitative estimation problem to determine the exact amount of solar energy that can be generated in a particular area. However, such approaches require extensive meteorological observations and long-term irradiance measurements, which are often limited or unavailable in many regions, especially in developing and archipelagic countries such as Indonesia. Therefore, this study simplifies the problem into a binary classification task that distinguishes between potential and non-potential areas for solar panel installation. This formulation enables the model to efficiently utilize spatial patterns from satellite imagery as an initial large-scale screening step before more detailed quantitative energy assessments are conducted.

Recent advancements in remote sensing and artificial intelligence have enabled more efficient and data-driven approaches to spatial energy assessment [9]-[10]. In recent years, numerous techniques have been applied to extract PV panels from remote sensing data. Conventional approaches involve region–line primitive association analysis and template matching [11], as well as machine learning algorithms such as support vector machine (SVM) classifiers [12] and random forest classifiers [13]-[14].

In particular, Convolutional Neural Networks (CNNs) have demonstrated remarkable capability in extracting spatial and texture-based features from satellite imagery, making them highly suitable for land-use classification, terrain analysis, and energy resource identification [15]-[17]. Despite the growing number of studies integrating deep learning with geospatial data, research focusing on large-scale, island-based solar potential mapping within the Indonesian context remains limited [18]. The lack of standardized datasets and spatially adaptive models limits the accuracy and scalability of current mapping frameworks [19].

This study addresses these challenges by developing a CNN-based model to identify potential solar panel installation areas using high-resolution satellite imagery across multiple Indonesian islands. The main objectives are: (1) to develop a CNN model capable of identifying visual characteristics indicative of solar suitability; (2) to evaluate the model's accuracy and computational efficiency in comparison with conventional classification methods; and (3) to generate spatial recommendations for solar infrastructure planning to support sustainable energy development.

The contributions of this research are to introduce a deep learning framework for solar energy mapping that integrates spatial and visual indicators derived from satellite imagery. In addition, this study provides a comparative evaluation between CNN and traditional machine learning models for solar site classification. Practically, it produces spatial recommendations for strategic solar installation planning in Indonesia, contributing to national renewable energy initiatives.

The rest of this paper is organized as follows. Section 2 presents the materials and methods, including dataset collection, preprocessing, and the design of the CNN architecture. Section 3 discusses the results and comparative analysis. Section 4 concludes the paper and highlights future research directions.

## 2. Research Method

Figure 1 illustrates the overall workflow of the proposed framework for solar potential mapping using satellite imagery and Convolutional Neural Network (CNN) modeling. The process consists of four main stages: Dataset Collection, Dataset Pre-processing, CNN Model Development, and Model Evaluation and Verification. In the Dataset Collection stage, satellite imagery data were obtained from Google Earth Engine using Sentinel-2 with a spatial resolution of 10 meters. This dataset provides multispectral information that captures the spatial and environmental variability of different regions across Indonesian islands. The Dataset Pre-processing stage involves several essential operations, including image cropping, normalization, and augmentation, to ensure data consistency and enhance model generalization. This step also includes the labeling of regions based on their suitability for solar panel installation, which serves as the ground truth for model training. In the CNN Model Development stage, a deep learning architecture, specifically VGG19, is utilized to extract spatial and textural features from the satellite imagery. The model is trained to classify land areas into potential and non-potential zones for solar energy installation, based on visual characteristics such as land reflectance, surface texture, and shading patterns. Finally, the Model Evaluation and Verification stage assesses the model's performance using standard metrics, including accuracy, precision, recall, and F1-score. Comparative analysis is also performed between the proposed CNN model and conventional classification methods to validate the reliability and effectiveness of the framework.

### 2.1 Dataset Collection and Pre-processing

In this study, the Sentinel-2 multispectral satellite imagery obtained from Google Earth Engine (GEE) was used as the primary data source. Sentinel-2, developed by the European Space Agency (ESA), provides high-resolution optical imagery with 13 spectral bands, ranging from visible to shortwave infrared wavelengths (443–2190 nm). The imagery offers 10 m, 20 m, and 60 m spatial resolutions, enabling accurate observation of land cover characteristics relevant to solar energy potential analysis.

For this research, imagery with 10 m spatial resolution (Bands 2, 3, 4, and 8 corresponding to Blue, Green, Red, and Near-Infrared) was selected due to its optimal balance between spatial detail and computational efficiency. The data acquisition covered multiple islands in Indonesia, including Java, Sumatra, Sulawesi, and Nusa Tenggara, representing diverse geographic and ecological conditions such as coastal areas, agricultural land, forest zones, and urban regions. Each selected scene underwent cloud masking and atmospheric correction using the Sentinel-2 Surface Reflectance (S2_SR) product in GEE to minimize noise caused by atmospheric scattering and cloud interference.

Afterward, the satellite imagery was cropped and divided into smaller image tiles of 256 × 256 pixels using an image tiling approach. This process facilitates efficient model training by converting large satellite scenes into manageable input patches while preserving spatial characteristics relevant to solar installation suitability analysis. In this study, the tiling process is used solely as a preprocessing step and should not be interpreted as semantic segmentation.

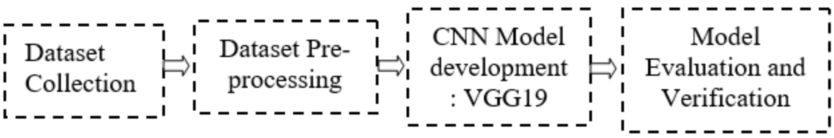


*Figure 1. The Proposed Framework*

The labeling process was conducted through manual visual interpretation of Sentinel-2 imagery combined with supporting geospatial information. The annotation was performed by members of the research team with experience in remote sensing and geospatial data analysis. Several criteria were used to determine the suitability of each tile for solar panel installation. Areas characterized by relatively high surface brightness, low vegetation density, homogeneous land cover, and gentle terrain slopes were labeled as Potential, as these conditions indicate open land surfaces suitable for solar infrastructure. Conversely, regions with dense vegetation cover, highly heterogeneous land patterns, or steep slopes were labeled as Not Potential, since such conditions may limit solar panel installation feasibility. Terrain slope information was obtained from Digital Elevation Model (DEM) data to support the identification of relatively flat areas suitable for solar energy infrastructure.

The resulting dataset consisted of 4,000 labeled image tiles, divided into training (70%), validation (20%), and testing (10%) subsets. The final dataset consists of 4,000 labeled image tiles, categorized into two classes: Potential and Not Potential areas for solar panel installation, as described in Table 1. To reduce classification bias, the dataset was constructed with a relatively balanced distribution between the two classes. Specifically, 2,050 tiles were labeled as Potential and 1,950 tiles as Not Potential. The dataset was collected from several Indonesian islands to represent diverse geographical conditions. These include Java, Sumatra, Sulawesi, and Nusa Tenggara. The distribution of tiles across regions was designed to capture variations in land cover characteristics and environmental conditions. The dataset distribution shows that the number of samples in both classes is relatively balanced, which helps prevent bias during model training and ensures that the classifier learns representative patterns for both categories.

This dataset structure ensures balanced representation across various terrains and land-use types, enabling robust model generalization. Figure 2 is a sample illustration showing examples of Sentinel-2 imagery used in the study. Each tile corresponds to a 256 × 256 px region extracted from different geographic settings in Indonesia.

*Table 1. Distribution of Image Tiles Across Regions and Classes*

| Region | Potential | Not Potential | Total |
|---|---|---|---|
| Java | 520 | 480 | 1000 |
| Sumatra | 520 | 480 | 1000 |
| Sulawesi | 500 | 500 | 1000 |
| Nusa Tenggara | 510 | 490 | 1000 |
| Total | 2050 | 1950 | 4000 |

### 2.2 CNN Model Development

The Convolutional Neural Network (CNN) model was developed to classify land areas from satellite imagery into two categories: suitable and unsuitable for solar panel installation. In this study, the VGG19 architecture was adopted as the backbone model due to its proven performance in image recognition tasks and its ability to capture both local and global spatial features. The VGG19 model consists of 19 weighted layers, including 16 convolutional layers and 3 fully connected layers, arranged in a sequential pattern with small receptive filters of size 3×3. VGG19 was selected as the backbone architecture due to its strong capability in hierarchical feature extraction and its proven performance in various image classification tasks. Although VGG19 is known to have relatively high computational complexity, the use of transfer learning with pre-trained ImageNet weights significantly reduces the training time and improves convergence. In addition, the availability of well-established pre-trained weights makes VGG19 a reliable architecture for extracting spatial features from satellite imagery, which is essential for identifying land characteristics relevant to solar panel installation. This configuration allows the model to extract fine-grained spatial details such as surface reflectance, vegetation texture, and shadow intensity, all of which are relevant indicators for solar suitability analysis [20]. The top classification layer of the original VGG19 network was replaced with a custom dense layer configuration consisting of: a flatten layer to convert 2D feature maps into 1D vectors, a dense (fully connected) layer with 512 neurons and ReLU activation, dropout layer (rate = 0.5) to prevent overfitting, and output layer with a single neuron and sigmoid activation for binary classification output [21].

Although VGG19 is an earlier deep learning architecture, it remains widely used in image classification tasks due to its stable design and strong hierarchical feature extraction capability. The architecture employs sequential convolutional layers with small receptive fields (3×3), which enables effective learning of spatial patterns from image data. In addition, the availability of pre-trained weights from the ImageNet dataset facilitates transfer learning, allowing the model to converge faster even with relatively limited training data. Compared with more recent architectures such as ResNet or MobileNet, VGG19 offers a simpler and well-understood structure that serves as a reliable baseline for evaluating deep learning approaches in satellite imagery analysis.


*Figure 2. Examples of Sentinel-2 imagery*

Additionally, transfer learning was employed by initializing the convolutional layers with pre-trained weights from ImageNet, enabling faster convergence and improved feature representation [22]-[24]. The final model was fine-tuned using satellite imagery data to adapt to domain-specific characteristics. The training process was conducted using TensorFlow and Keras frameworks with the following configuration parameters in Table 2.

*Table 2. The Hyperparameters*

| Hyperparameter | Input |
|---|---|
| Optimizer | Adam |
| Learning rate | 0.0001 |
| Loss function | Binary Cross-Entropy |
| Batch size | 32 |
| Epochs | 100 |

| | |
|---|---|
| Validation split | 20% of training data |
| Early stopping | applied to prevent overfitting when validation loss stagnates |

### 2.3 Model Evaluation and Verification

To assess the performance and reliability of the developed CNN model in classifying satellite imagery for solar potential mapping, a comprehensive evaluation procedure was conducted. This evaluation aimed to measure the model's ability to correctly identify suitable and unsuitable areas for solar panel installation through a combination of quantitative performance metrics and qualitative visual verification.

The model evaluation follows the dataset partition defined during preprocessing, which divided the dataset into 70% training, 20% validation, and 10% testing subsets. Each subset contains distinct image tiles to ensure no overlap among the training, validation, and testing data. The dataset split was performed before the training process to avoid potential data leakage between the subsets.

Performance was measured using four key metrics commonly applied in image classification research, as expressed in Equations 1–4 [25]:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$F1 - \ Score = 2x \frac{Precision \times Recall}{Precision + Recal} \tag{4}$$

where TP, TN, FP, and FN denote the numbers of true positives, true negatives, false positives, and false negatives, respectively. These metrics collectively provide a robust measure of both classification accuracy and generalization capability of the model. A confusion matrix was generated to provide deeper insight into classification errors. The model with segmentation produced fewer false positives (incorrectly labeling unsuitable areas as suitable) than the baseline model. This improvement confirms that segmentation effectively reduces noise and enhances the distinctiveness of land features, especially in areas with mixed land cover types.

## 3. Results and Discussion

This section presents and discusses the outcomes of the CNN-based solar potential mapping, including the spatial distribution of predicted solar-suitable areas, comparative performance analyses across different architectures, and interpretations of the results in relation to geographic and environmental factors. The CNN model was applied to satellite imagery datasets collected from multiple Indonesian islands, including Java, Sumatra, Sulawesi, Kalimantan, and Nusa Tenggara. The classification output identifies areas with high solar installation suitability based on surface reflectance, land texture, and environmental consistency. The experimental results revealed that the VGG19 model with segmentation-based pre-processing achieved the most stable and accurate predictions. This configuration showed enhanced capability to suppress irrelevant background features and improve classification homogeneity across diverse geographic conditions.

Figure 3 presents the training results of the model, including the variations in loss, accuracy, F1-score, and the train–validation loss gap over 100 epochs. Based on the Training & Validation Loss plot, both training and validation loss values decrease sharply during the initial epochs and reach very low levels after around the 20th epoch. The two curves exhibit almost identical patterns, indicating that the model learns effectively without signs of overfitting. The Validation Accuracy graph shows a rapid improvement, reaching nearly 1.0 early in training and remaining stable throughout, suggesting excellent generalization performance on the validation dataset. Similarly, the Validation F1-Score remains consistently around 1.0, indicating a perfect balance between precision and recall. Meanwhile, the Train Validation Loss Gap plot demonstrates that the difference between training and validation loss stays well below the warning threshold after the initial epochs, confirming that overfitting does not occur. Overall, these results indicate that the model achieves rapid convergence with highly stable and superior performance, capable of classifying validation data with exceptional accuracy. Furthermore, the preprocessing strategy based on image tiling enables the model to focus on localized spatial patterns from satellite imagery, which helps improve the identification of land surface characteristics relevant to solar panel installation suitability.

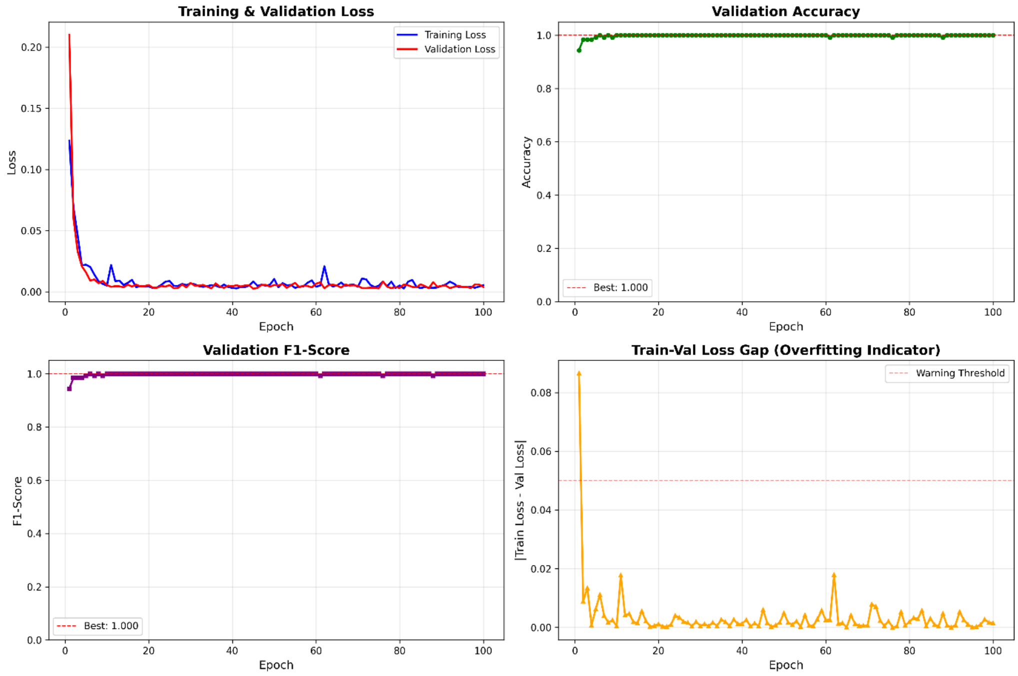


*Figure 3. Training and Validation Loss*

The dataset used in this study includes satellite imagery collected from several Indonesian islands, including Java, Sumatra, Sulawesi, Kalimantan, and Nusa Tenggara. To illustrate the model's classification performance across different geographic characteristics, two representative regions, Yogyakarta (Java) and Aceh (Sumatra) are presented in Figure 4. These regions were selected because they represent contrasting land surface conditions, ranging from relatively homogeneous urban–agricultural landscapes to more heterogeneous terrain structures.

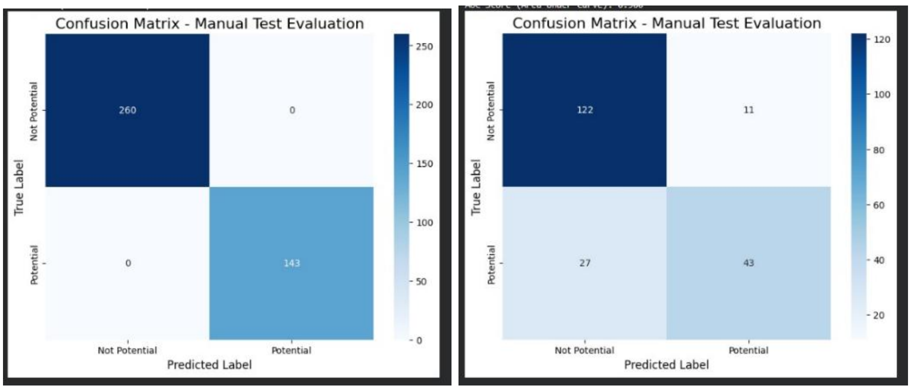


*Figure 4. Confusion Matrix for Yogyakarta and Aceh Sentinel-2* imagery

Figure 4 shows the confusion matrices for model evaluation using Sentinel-2 imagery in two different regions, i.e., Yogyakarta (left) and Aceh (right). These matrices illustrate the model's performance in classifying areas as Potential or Not Potential based on the ground truth labels. In the Yogyakarta dataset (left matrix), the model achieved perfect classification performance, where all samples were correctly predicted. Specifically, 260 samples labeled as Not Potential were correctly classified, and 143 samples labeled as Potential were also accurately identified, resulting in no false positives or false negatives. This indicates that the model generalizes exceptionally well within the Yogyakarta region, demonstrating both 100% accuracy and precision for both classes. The clean diagonal pattern in the matrix confirms the model's robustness and reliability when applied to this dataset.

Conversely, in the Aceh dataset (right matrix), the performance shows a slight decline compared to Yogyakarta. The model correctly identified 122 Not Potential samples and 43 Potential samples. However, 27 Potential samples were misclassified as Not Potential, and 11 Not Potential samples were incorrectly labeled as Potential. These misclassifications suggest that the model faced challenges adapting to the spectral or environmental differences in

Aceh's imagery, which may vary in surface characteristics, lighting conditions, or data distribution compared to Yogyakarta. Despite these errors, the overall classification accuracy remains relatively high, and the diagonal dominance of the matrix indicates that the model retains good predictive capability.

It can be concluded that the model achieved excellent classification performance on the Sentinel-2 imagery for the Yogyakarta region, with perfect accuracy and no misclassifications. This indicates that the model effectively recognized the distinguishing features between potential and non-potential areas in that region. However, the model's performance slightly decreased when applied to the Aceh dataset, where several misclassifications occurred between the Potential and Not Potential classes. This difference suggests the presence of spatial or spectral variations between regions that affect the model's generalization capability. Overall, the model demonstrates strong and reliable performance in detecting potential areas, but further refinement, such as fine-tuning or domain adaptation, is recommended to ensure consistent results across diverse geographic conditions. Based on the evaluation results derived from the confusion matrix and classification metrics, the proposed VGG19-based model achieved an overall classification accuracy of 94.2% in distinguishing between potential and non-potential areas for solar panel installation.

The experimental results indicate that the proposed VGG19-based model is capable of effectively capturing spatial patterns associated with solar panel installation suitability. Satellite imagery contains various visual cues, such as land surface brightness, vegetation density, and texture homogeneity, which can be learned by deep convolutional layers during training. The use of transfer learning with pre-trained ImageNet weights allows the model to extract meaningful features even with a relatively limited dataset. In addition, the tiling-based preprocessing approach enables the model to focus on localized spatial characteristics within satellite imagery, which helps improve classification accuracy when distinguishing between suitable and unsuitable regions.

From an application perspective, the proposed approach provides a scalable tool for preliminary solar site screening across large geographic areas. Instead of relying solely on extensive field measurements or long-term meteorological observations, satellite imagery combined with deep learning can support rapid identification of candidate locations for solar infrastructure planning, particularly in regions with limited monitoring infrastructure.

## 4. Conclusion

This study presents a deep learning-based approach for mapping solar energy potential using satellite imagery, focusing on the diverse geographical landscapes of Indonesia. By integrating Convolutional Neural Network (CNN) architectures with a preprocessing strategy based on image tiling, the proposed method successfully identifies suitable areas for solar panel installation with high spatial accuracy and computational efficiency. Among the evaluated configurations, the VGG19-based classification model trained on tiled satellite imagery achieved the best overall performance, reaching an accuracy of 94.2% in identifying areas suitable for solar panel installation.

The experimental results demonstrate that the tiling-based preprocessing strategy enables the model to focus on localized spatial patterns in satellite imagery, which improves the model's ability to distinguish between suitable and unsuitable land surfaces. Spatial verification across several Indonesian regions, including Java, Sumatra, Sulawesi, Kalimantan, and Nusa Tenggara, further indicates that the model can capture relevant land surface characteristics associated with solar energy suitability. These findings highlight the potential of CNN-based spatial analysis as a scalable and data-driven approach for preliminary solar energy site identification, particularly in regions where comprehensive meteorological monitoring infrastructure is limited.

Future research will focus on expanding the dataset through multi-temporal satellite imagery integration and incorporating Digital Elevation Models (DEM) to account for terrain shading effects and topographic variability that may influence solar energy potential. The integration of multi-temporal observations is expected to improve the robustness of the model by capturing seasonal variations in land cover, atmospheric conditions, and surface reflectance. Additionally, coupling the CNN framework with GIS-based optimization techniques and energy yield simulations could further refine site selection strategies for large-scale photovoltaic installations, enabling more accurate estimation of energy production potential.

From a methodological perspective, future studies will also explore the use of more recent and computationally efficient deep learning architectures, such as ResNet, EfficientNet, and MobileNet, to evaluate their potential in improving classification performance while reducing computational complexity. Investigating these architectures may provide a better balance between model accuracy and efficiency when applied to large-scale geospatial datasets. Ultimately, these developments are expected to advance renewable energy mapping methodologies and support Indonesia's strategic transition toward sustainable, decentralized, and data-driven solar energy development.

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