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UNDERGRADUATE PROJECT FINAL REPORT

Project Title:	**Cloud Detection and Classification in Radiance Sky Images for Solar Energy Optimization Using Attention-SolarNet**
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BSc (Single Honours) Degree Project

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A report submitted as part of the requirements for the degree of BSc (Hons) in Software Engineering

At

Chengdu University of Technology Oxford Brookes College

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Abstract

Accurate cloud detection and classification are essential for optimizing solar energy systems, as clouds cause significant fluctuations in solar irradiance, directly impacting photovoltaic (PV) efficiency. This project introduces Attention-SolarNet, a deep learning-based model that combines a Convolutional Neural Network (CNN) with a spatial attention mechanism to improve cloud detection in radiance sky images. The attention mechanism dynamically highlights cloud-relevant regions, enhancing classification accuracy and interpretability. The project utilizes the NWPU-RESISC45 dataset, comprising 31,500 sky images, and employs data preprocessing techniques, including normalization and augmentation, to ensure robust model training. Experimental results demonstrate that Attention-SolarNet outperforms traditional CNN models, achieving a validation accuracy of 93.10%, test recall of 100%, and test F1-score of 94.00%, with significantly reduced test loss (14.89% vs. 73.72% for SolarNet). The model's superior performance is further validated through precision-recall trade-offs, ROC analysis, and Grad-CAM visualizations, confirming its ability to generalize across diverse cloud formations. By addressing challenges such as data imbalance and computational complexity, Attention-SolarNet enables more reliable solar irradiance forecasting, supporting real-time energy management and grid stability. This project contributes to renewable energy optimization by advancing cloud classification techniques, reducing energy storage costs, and improving solar power predictability. Future work will explore hybrid architecture and larger datasets to further enhance model efficiency for real-world deployment.

***Keywords*:**

Cloud detection, Solar energy optimization, Attention Mechanisms, Convolutional Neural Network (CNN), Deep learning, Solar irradiance forecasting, Image classification, Renewable energy management

Abbreviations

CNN	Convolutional Neural Network
ATT-CNN	Attention-based Convolutional Neural Network
ResNet	Residual Network
PV	Photovoltaic
ML	Machine Learning
DL	Deep Learning
RMSE	Root Mean Square Error
TP	True Positive
TN	True Negative
FP	False Positive
FN	False Negative
ReLU	Rectified Linear Unit
Acc	Accuracy
Prec	Precision
Spec	Specificity
Para	Parameters
F1	F1-Score
Rec	Recall
LR	Learning Rate
ROC	Receiver Operating Characteristic
AUC	Area Under the Curve
Grad-CAM	Gradient-weighted Class Activation Mapping
NWPU-RESISC45	Northwestern Polytechnical University Remote Sensing Image Scene Classification dataset

Glossary

Cloud Detection: The process of identifying cloud formations in sky images to predict solar irradiance fluctuations.

Attention Mechanism: A neural network component that dynamically weights feature importance to enhance model focus on relevant regions.

Solar Irradiance: The power per unit area received from the sun, critical for solar energy systems.

Data Augmentation: Techniques to artificially expand training datasets by applying transformations (e.g., rotation, flipping).

Binary Crossentropy: A loss function used for binary classification tasks, measuring prediction errors.

Grid Stability: The ability of an energy grid to maintain consistent power supply despite variability in renewable sources.

1 Chapter 1 Introduction

1.1 Background

Clouds significantly affect the amount of solar radiation reaching the Earth's surface, making accurate cloud detection and classification crucial for solar energy optimization[1]. Research indicates that clouds are the primary factor responsible for fluctuations in solar irradiance, directly impacting the efficiency of photovoltaic (PV) systems [2]. The variability caused by clouds can lead to significant deviations in energy production, posing challenges for grid management and energy reliability [3].

The impact of clouds on solar energy generation has been well-documented. For instance, studies have shown that the presence of clouds can reduce solar irradiance by up to 80%, leading to substantial drops in energy output from PV systems [2], [4]. Understanding cloud patterns is, therefore, essential for solar energy systems to manage and mitigate these fluctuations. Accurate cloud detection enables predictive modeling of solar irradiance, which is crucial for optimizing the operation of solar power plants [1].

With solar energy becoming one of the most prominent renewable energy sources globally, effective management of these fluctuations is essential to ensure reliable energy output [5]. Recent advancements in machine learning (ML) and deep learning (DL) have provided powerful tools to address these challenges, enabling more precise cloud detection and classification from radiance sky images [6]. These methods help optimize solar energy production by predicting irradiance more effectively, which is critical for integrating solar power into the energy grid [7].

Furthermore, various studies have illustrated the effectiveness of machine learning techniques in processing and analyzing satellite and ground-based imagery for cloud classification [8]. Techniques such as Convolutional Neural Networks (CNNs) have shown promise in automating the cloud classification process, achieving higher accuracy and efficiency compared to traditional methods [9]. This is particularly relevant in the context of increasing reliance on solar energy, where accurate forecasting is essential for enhancing energy generation strategies and ensuring grid stability [1].

1.1.1 Risks

The primary risks in cloud detection and classification involve potential inaccuracies that can significantly impact solar energy systems. Jiang et al. [8] mentioned that misclassification of cloud types can lead to substantial prediction errors in solar irradiance, resulting in economic losses and inefficient energy management. Further, technical risks include model failure under complex atmospheric conditions, inability to generalize across different geographic regions, and potential computational limitations that prevent real-time cloud detection. False positive or negative cloud classifications can also cause critical miscalculations in solar power forecasting, potentially disrupting grid stability and renewable energy planning [10].

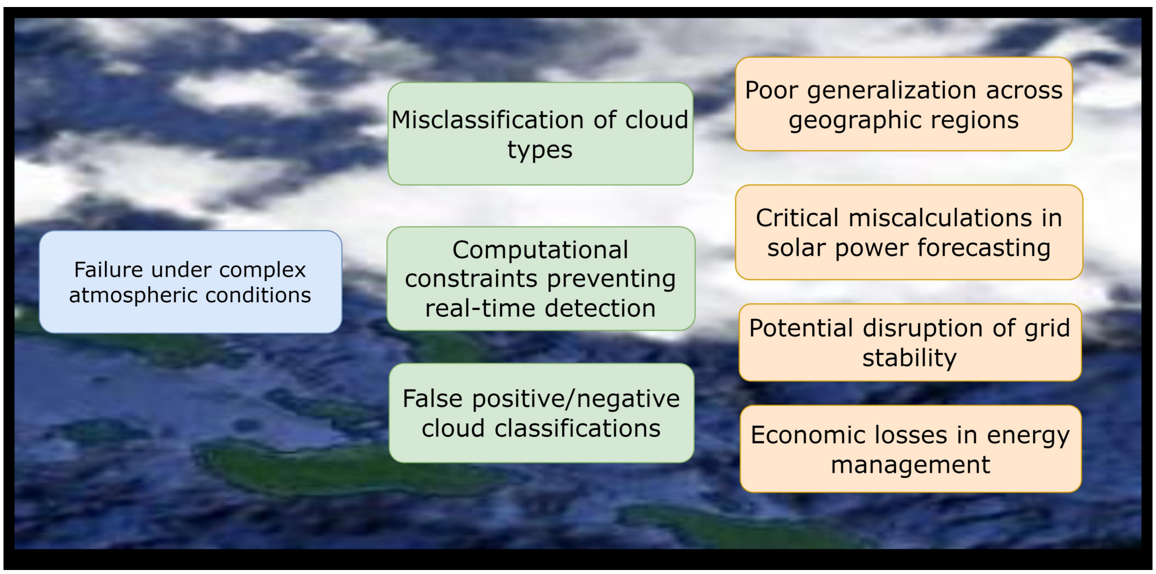


Figure1. Risk and Factors in Cloud Detection and Classification for Solar Power Optimization

1.1.2 Challenge

Key challenges center on the complex technological and environmental barriers in cloud detection. The inherent variability of cloud morphology demands sophisticated image processing algorithms capable of distinguishing subtle atmospheric transitions. Deep learning models must overcome limitations in training data diversity, ensuring robust performance across varied climatic conditions. Advanced computational techniques are required to handle high-dimensional data from radiance sky images, processing multiple spectral and textural features simultaneously. Additionally, the project must develop adaptive algorithms that can quickly interpret dynamic atmospheric changes, integrating multiple detection methodologies to enhance classification accuracy and reliability in solar energy optimization contexts.

1.2 Aim

The aim of this project is to develop a deep learning-based (CNN) system that can accurately detect and classify cloud formations in radiance sky images. This system will improve solar energy generation by predicting fluctuations in solar irradiance, contributing to more efficient energy production and grid management.

1.3 Objectives

- Collect sky image datasets for training and testing.
- Develop preprocessing techniques to enhance image quality, segment cloud regions, and normalize data for machine learning models.
- Design and implement deep learning models (e.g., Convolutional Neural Networks - CNNs) for cloud detection and classification.
- Evaluate the performance of models using metrics such as accuracy, precision, recall, and F1-score, ensuring robustness for real-time deployment.
- Integrate the models into a cloud-based platform that can forecast solar irradiance for energy systems.

1.4 Project Overview

The diagram presents a six-stage project timeline for developing SolarNet a Convolutional Neural Network and Attention-SolarNet models. It begins with a "Background View" stage to establish foundational knowledge. This is followed by "Dataset Collection" to gather necessary data. The third stage involves "Data Processing, Augmentation, and Special Balancing" to prepare the data for model training. The fourth stage is dedicated to "Model Design SolarNet and Attention-SolarNet," where the models are architected. The fifth stage, "Model Comparing and Explanation," evaluates and compares the models' performances. The final stage is "GUI Design," focusing on creating a user-friendly interface for the application.

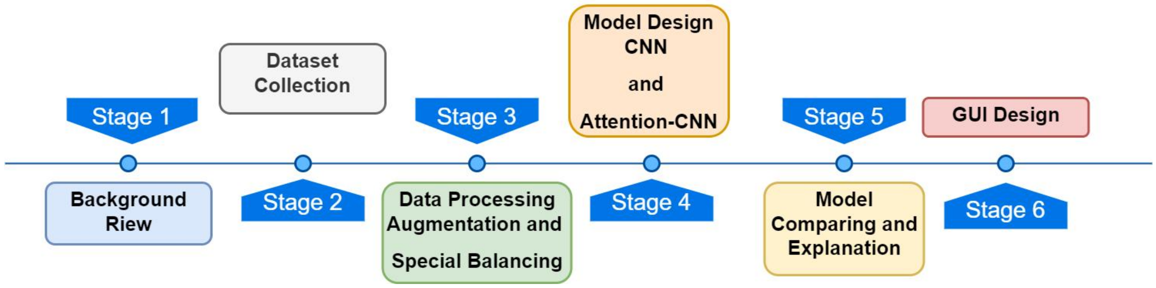


Figure 2. Project Overview

1.4.1 Scope

This project focuses on cloud detection and classification using radiant sky images to optimize solar energy production. Through deep learning techniques, the project aims to develop the Attention-SolarNet model that provide accurate cloud classification and solar irradiance predictions. By improving the forecasting of solar irradiance, the project addresses key challenges in solar energy reliability and contributes to more sustainable and optimized energy systems. The significance of this study lies in enhancing the accuracy of cloud detection models and making solar energy generation more predictable, which is essential for reducing energy variability.

The following are the significances of this project and potential contributions:

- Optimization of Solar Energy Infrastructure
- Real-Time Energy Management
- Reduction in Energy Storage Costs
- Supporting Grid Stability
- Environmental and Economic Impact
- Advanced Cloud Classification Techniques
- Novel Dataset Applications
- Interdisciplinary Knowledge Sharing
- Prototype for Scalable, Cloud-Based Solutions
- Improvement in Real-World Solar Energy Systems

- Support for Renewable Energy Policies

1.4.2 Audience

- **Energy Companies and Solar Power Plant Operators:**

  Energy companies and solar plant operators stand to benefit from more accurate solar irradiance forecasts, enabling them to optimize energy production, improve efficiency, and better manage resources. Enhanced cloud classification models will help these stakeholders reduce costs associated with energy variability and storage, making solar energy more reliable and cost-effective.

- **Grid Managers and Energy Storage Providers:**

  For grid managers, improved cloud detection translates to better integration of solar power into the energy grid. More consistent irradiance predictions allow for smoother load balancing and fewer interruptions, supporting a stable energy supply. Energy storage providers can also benefit by reducing the need for over-provisioned storage systems, as more accurate forecasting minimizes sudden dips or surges in solar energy.

- **Researchers in Renewable Energy, Meteorology, and AI:**

  Researchers across renewable energy, meteorology, and artificial intelligence fields can leverage this study's findings to advance their own work in energy forecasting, environmental monitoring, and cloud pattern recognition. The project contributes new methods and models to the scientific community, potentially fostering further interdisciplinary collaboration and innovation.

- **Policymakers and Environmental Regulator:**

  Policymakers aiming to expand renewable energy and reduce greenhouse gas emissions can use the insights from this study to support more effective policies and infrastructure planning. Reliable solar energy predictions contribute to a more sustainable energy landscape, helping policymakers justify investments in solar technology and grid enhancements that prioritize renewables.

- **Investors in Renewable Technology and Infrastructure:**

  Investors focused on renewable technology and infrastructure development can benefit from the improved reliability and efficiency that this project promises for solar energy. Enhanced forecasting and grid stability can make solar energy ventures more attractive, supporting the growth and adoption of clean energy technologies in the market.

2 Chapter 2 Background Review

Cloud detection and classification are critical for optimizing solar energy production, and various methods have been developed to improve accuracy and efficiency in this field. This section presents a literature review of notable research contributions.

2.1 Traditional Method

Traditional methods for cloud detection and classification have long relied on satellite imagery, meteorological observations, and manual image analysis. These approaches typically involve monitoring cloud cover and estimating solar irradiance using data from ground-based sensors and satellites. For example, early methods for cloud classification were often based on visual inspection of satellite images, where meteorologists manually categorized cloud types based on visible features. However, these techniques are limited by the inherent subjectivity of human interpretation and are prone to inconsistencies. As a result, they are less scalable and unsuitable for real-time cloud detection, which is essential for optimizing solar energy production.

Figure 3. Traditional Method for Cloud Detection and Classification

Researchers such as Fabel et al. [11] and Aakroum et al. [12] have demonstrated how traditional methods fall short in handling the complexity and dynamic nature of cloud formations. These techniques rely heavily on human judgment and are often slow, making them ill-suited for applications that require rapid, automated classification, such as solar irradiance prediction. Moreover, these approaches struggle to account for spatial relationships and temporal variations in cloud patterns, further limiting their effectiveness.

Despite these challenges, traditional approaches laid the groundwork for the development of automated cloud classification systems. They helped to establish initial frameworks for using satellite data and ground-based sensors, which were later improved upon by machine learning and deep learning methods. These early models provided essential insights into cloud detection and solar irradiance prediction, providing a foundation for more advanced, automated methods that are more accurate and efficient.

2.2 Machine Learning Approach

The introduction of machine learning (ML) has significantly advanced cloud detection and classification by automating the process of identifying cloud patterns and classifying different cloud types from satellite and sky imagery. ML techniques, such as supervised learning algorithms, have demonstrated improvements over traditional methods by processing large datasets efficiently and identifying complex patterns. For instance, Aakroum et al. [12] used a deep neural network combined with mini-batch k-means clustering to predict solar irradiance from sky imagery, achieving 99.7% accuracy. N. Mandal and T. Sarode [4] Developed a machine learning framework for cloud cover prediction using data imputation techniques, highlighting ML's potential in solar energy optimization.

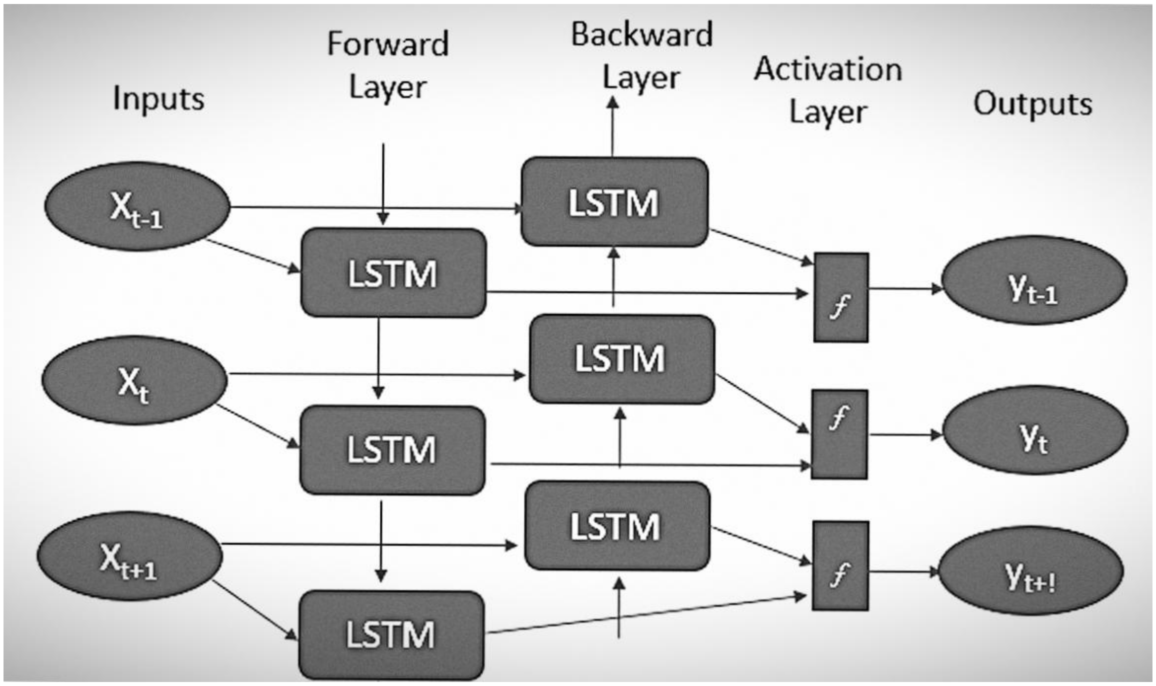


Figure 4. Machine Learning Model with LSTM from N. Mandal and T. Sarode [4]

Despite these successes, machine learning models typically require significant feature engineering and may not fully capture the intricate spatial relationships present in cloud images, which deep learning models are better equipped to address.

2.3 Deep Learning Approach

Deep learning (DL) has emerged as a powerful technique for cloud detection and classification tasks, providing significant improvements in accuracy and efficiency compared to both traditional methods and machine learning models. Deep learning models, particularly Convolutional Neural Networks (CNNs), automatically extract hierarchical features from images, making them ideal for complex image classification tasks, including cloud detection. These models have the ability to learn from large datasets of labeled cloud images and can handle high-dimensional, spatially complex data more effectively than traditional ML models.

Rajagukguk et al. [13] implemented an LSTM-based model to forecast cloud cover from sky images, which significantly reduced the root mean square error (RMSE) under high-variability conditions, a key factor for solar irradiance prediction. Similarly, Li et al. [14] used a deep learning approach on Himawari-8 satellite images, achieving 98.6%

accuracy in classifying thin and multilayer clouds, outperforming traditional models such as MODIS.

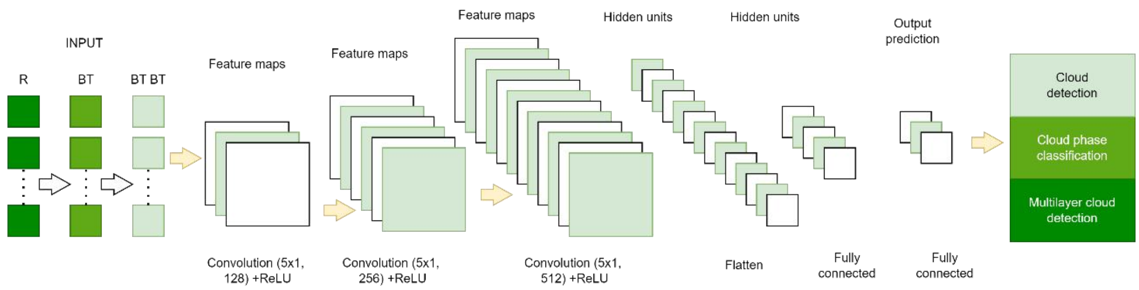


Figure 5. Multiple Input CNN Model from Li et al. [14]

2.3.1 CNN

CNNs have proven to be highly effective in image-based tasks, particularly in cloud detection and classification for solar energy optimization. CNNs consist of multiple convolutional and pooling layers that automatically detect features such as edges, textures, and shapes, which are crucial for recognizing cloud patterns. Several studies have demonstrated the utility of CNNs in cloud classification. For instance, Šinko et al. [15] used an improved CNN model trained on cloud image datasets, achieving an accuracy of 85% for cloud type classification. Wang et al. [16] developed a CNN-based cloud classification model, CloudA, which achieved an impressive 98.63% accuracy using the SWIMCAT dataset. These studies highlight CNNs' ability to perform automated, high-accuracy cloud classification, demonstrating their potential in optimizing solar energy production.

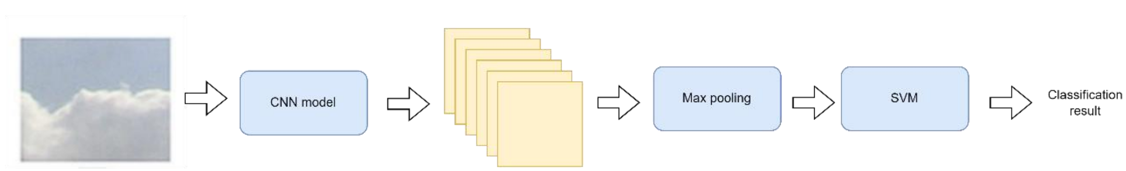


Figure 6. CNN model with SVM method from Wang et al. [16]

2.3.2 Attention CNN Mechanism

Attention mechanisms have been integrated into CNNs to further enhance their ability to focus on the most relevant regions of an image, which is especially useful in cloud detection tasks. Attention mechanisms help the model concentrate on the cloud formations, ignoring irrelevant background details, thereby improving classification accuracy. This approach has proven beneficial in complex image classification tasks where certain regions of an image (such as cloud formations) are more important than others for the final prediction. The integration of attention mechanisms in CNNs has been shown to improve the predictive modeling of solar irradiance by providing more accurate cloud classifications. For instance, research by Jonathan et al. [17] introduced a CNN learning model using attention mechanisms, They mentioned that ATT_CNN can use long image histories to do better, unlike some benchmarks that stop improving, this shows how important local visual data is. Overall, this work proves that attention-based CNNs are good at predicting solar irradiance using sky camera images. These improvements underscore the significant role that attention-based CNNs can play in cloud detection and solar energy optimization.

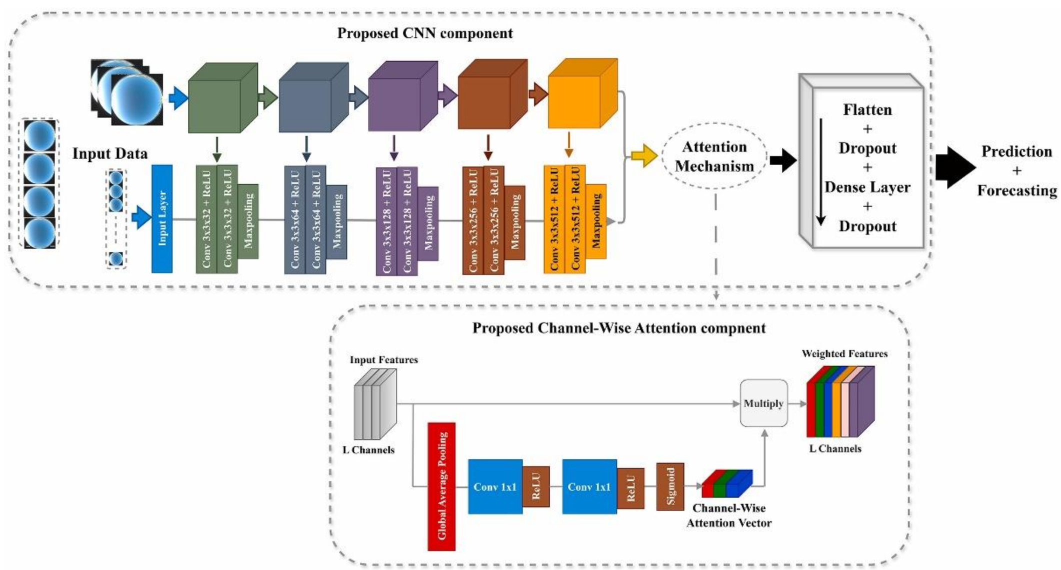


Figure 7. Attention CNN Model from Jonathan et al. [17]

A summary of the different researchers and their findings and possible results can be found in Table 1.

Author	Datasets	Methods & Models	Results	Limitation
Fabel et	300,000 all-sky	Self-supervised	95%	Lower spatial resolution, more

al.[11]	images	learning (CNN)		profound image distortion and vignetting near the horizon contribute to higher error rates in these image regions.
Aakroum et al.[12]	Fish-eye camera sky images	k-means clustering, DNN	99.7%	Spatial and temporal resolution limitations of satellite images.
Rajagukguk et al. [13]	Local sky camera images	LSTM, Deep Learning	RMSD reduced, high variability	-
Li et al. [14]	Himawari-8 satellite images	DNN, cloud phase discrimination	98.6%	Have limitations on the representativenes s of the diurnal characteristics of clouds.
Ye et al. [18]	Pixel-labeled sky images	Supervised fine-grained	90.97%	Limited data set.
Šinko et al. [15]	Ground-based images	CNN for cloud classification	85%	Insufficient amount of input images. Low dynamic range of input

				images.
Wang et al. [16]	SWIMCAT, total-sky datasets	CNN-based (CloudA)	98.63%	Overfitting situation of the model needs to be determined.
Jonathan et al. [17]	The National Renewable Energy Laboratory's (NREL) solar radiation research laboratory (SRRL) dataset	Attention-CNN	A notable decrease in RMSE values.	The model is sensitive to variations in input data.

Table 1: Summary of Related Works

3 Chapter 3 Methodology

3.1 Approach

This project employs an Attention-SolarNet as the core model for detecting and classifying cloud formations in radiant sky images. Convolutional Neural Network are particularly suitable for image-based tasks due to their ability to automatically learn spatial hierarchies through convolutional layers, which extract important features such as edges, textures, and shapes from image data [19].

3.2 Model Structure

The proposed Attention-SolarNet model as shown in Figure 8 is discussed in this section with its components specifically SolarNet and spatial Attention Mechanisms to solve intra-hour solar forecasting with cloud detection. The Attention-SolarNet, enhances SolarNet by integrating a spatial attention mechanism to dynamically focus on cloud-affected regions, improving classification accuracy and interpretability. Both models process input images of size 256×256×3 (RGB).

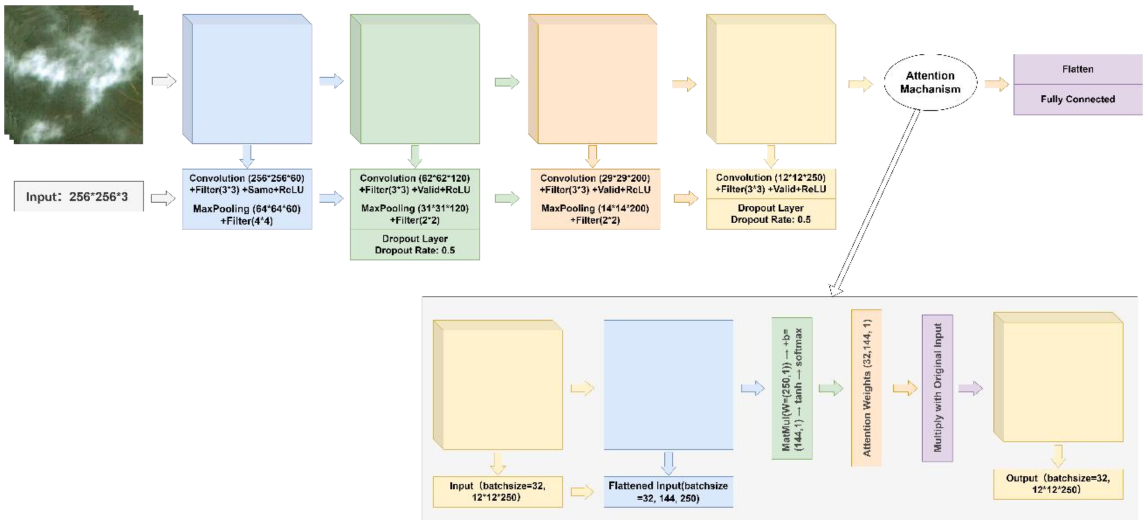


Figure 8: Attention-SolarNet Model for Cloud Detection

3.2.1 Attention Mechanism

The spatial attention mechanism is a machine-learning technique that enhances model accuracy by concentrating on relevant data and prioritizing crucial features over unimportant ones. The proposed approach in this study incorporates a custom attention layer within SolarNet. This custom attention layer processes the input feature maps by first applying a linear transformation through a learnable weight matrix, followed by the addition of a bias term. The transformed features are then passed through a hyperbolic tangent activation function to introduce non-linearity. Subsequently, a softmax activation function is applied across the time steps to normalize the attention scores into a probability distribution. This attention vector is multiplied elementwise with the original input features, dynamically adjusting the importance of each feature by highlighting significant aspects and suppressing less important ones. The resulting weighted features, enhanced by the attention mechanism, are then forwarded to the subsequent layers of the neural network for further processing. This custom attention layer acts like an intelligent filter that analyzes each feature of the input to understand their importance, then emphasizes the most relevant information for the task at hand. By incorporating this custom attention layer, the model's overall performance and feature representation are improved, making it more effective in cloud detection for solar energy optimization.

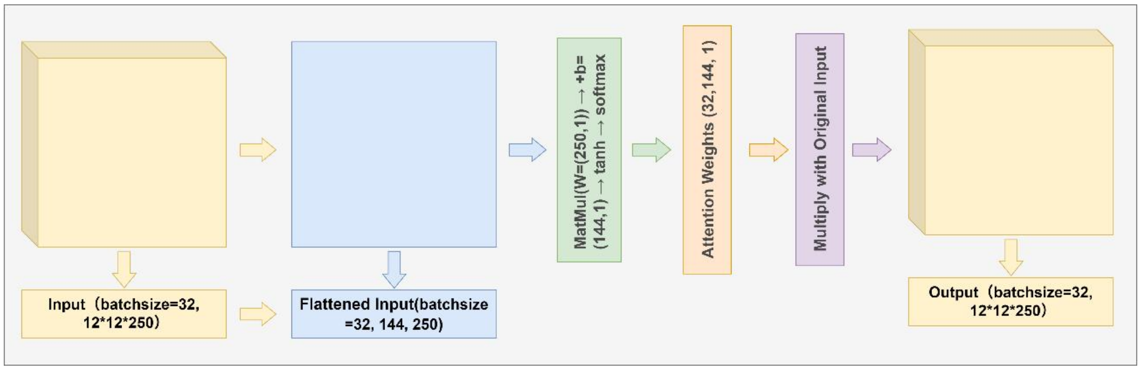


Figure 9: Attention Mechanism

For an input tensor 12*12*250 (batch of 32 images):

1. **Flatten Spatial Dimensions**:

$$X\_flat \text{ (where } 12 \times 12 = 144) \tag{1}$$

2. **Compute Attention Scores**:

$$e = tanh\ (X\_flat \cdot W + b) \tag{2}$$

where W means weight, b means bias

3. **Normalize Weights**:

$$a = softmax\ (e, axis{=}1) \tag{3}$$

4. **Apply Attention**:

$$Y = X\_flat \odot a \tag{4}$$

where $\odot$ is element-wise multiplication with broadcasting.

5. **Reshaping Output**:

$$Y\_out \tag{5}$$

where original spatial dimensions 12*12*250.

3.2.2 SolarNet Model

The SolarNet model processes input images of size 256×256×3 through a series of four convolutional blocks, each designed to hierarchically extract and compress features for cloud classification. The first block applies to 60 filters of size 3×3 with "same" padding and ReLU activation, producing feature maps of 256×256×60, followed by 4×4 max-pooling to reduce dimensions to 64×64×60. The second block uses 120 3×3 filters with "valid" padding, yielding 62×62×120 outputs, which are further down sampled by 2×2 max-pooling to 31×31×120. A dropout layer (rate=0.5) is then applied to mitigate overfitting. The third block employs 200 3×3 filters, reducing spatial dimensions to 29×29×200 before 2×2 max-pooling compresses them to 14×14×200. The fourth block convolves 250 3×3 filters to produce 12×12×250 features, followed by another dropout layer (rate=0.5). Finally, the features are flattened into a 36,000-dimensional vector and passed through a dense layer with 512 ReLU-activated units and a sigmoid-activated output layer for binary cloud classification. The model's fixed pooling operations, while efficient, may discard subtle cloud features, prompting the need for the attention-enhanced variant.

SolarNet model formula summary:

$$Y = \sigma(W_6 \cdot ReLU(W_5 \cdot Flatten(Dropout(F_4(P_3)) + b_5) + b_6) \quad (6)$$

Where:

b_5 for the 512-unit dense layer bias.

b_6 for the final classification bias.

Components:

1. Convolutional Blocks ($i = 1\ to\ 4$):

$$F_i = ReLU(W_i * P_{i-1} + b_i) \quad (7)$$

where $P_0 = X\ (input\ image)$

2. Pooling:

$$P_i = MaxPool_{ki} \times {}_{ki}\big(F_i\big), k_1 = 4, k_2 = k_3 = k_4 = 2 \quad (8)$$

3. Dropout:

$$Dropout(x) = \{\, x/0.5\ (prob = 0.5), 0\ (otherwise)\, \} \quad (9)$$

4. Classification:

$$Y = \sigma(W_6 D_1 + b_6) \quad (10)$$

Key Symbols:

- $\boldsymbol{\sigma}$: Sigmoid
- $*$: Convolution
- $\odot$: Element-wise multiply

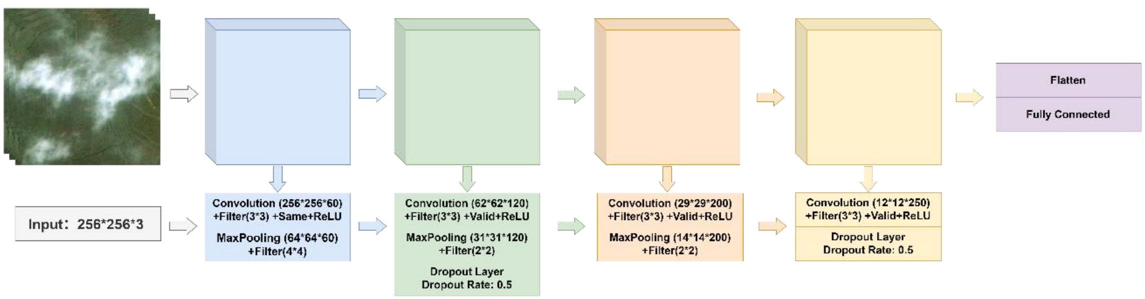


Figure 10: SolarNet Model for Cloud Detection

The SolarNet model was trained using consistent hyperparameters to ensure fair comparison with its attention-enhanced counterpart. The training process utilized RMSprop optimization with a learning rate of 1e-4, chosen for its stability in handling sparse gradients common in image classification tasks. A batch size of 32 balanced memory constraints and gradient estimation accuracy, while 30 epochs provided sufficient convergence time without overfitting. The model minimized binary crossentropy loss, appropriate for the cloud/no-cloud classification task, and tracked five metrics: accuracy, precision, recall, F1-score, and specificity, offering a comprehensive view of performance. Training data was fed via a generator that automatically rescaled images, with steps per epoch calculated as the total training samples divided by the batch size. The test set was evaluated at each epoch to monitor generalization, and data shuffling ensured robust gradient updates.

The training parameter data of SolarNet is shown in Table2 as follows:

Total params:	**19,166,075**

Trainable params:	**19,166,075**
Non-trainable params:	**0**

Table 2: SolarNet Model Summary

Although SolarNet captures spatial patterns effectively, it lacks an explicit mechanism for focusing on the most relevant regions of an image. This uniform treatment of all spatial features can reduce predictive accuracy in complex and heterogeneous environments. To overcome this limitation, a self-attention mechanism is introduced in the enhanced model, Attention-SolarNet.

3.2.3 Attention-SolarNet Model

To address these limitations, this project introduces Attention-SolarNet, an enhanced version of the base model that integrates a spatial attention mechanism to refine the feature selection process. The Attention-SolarNet model extends SolarNet by adding a spatial attention mechanism to dynamically highlight cloud-relevant regions. It processes input images of size 256×256×3 through the same four convolutional blocks as SolarNet, maintaining identical dimensions up to the final feature maps of 12×12×250. At this stage, instead of direct flattening, the model applies an attention layer to recalibrate spatial features. In the experiment, I attempted to add one attention layer after each convolutional layer ended. And attempted to add two attention layers after different convolutional layers ended. After multiple permutations and combinations, I tried 11 positions for adding attention layers. Finally, the experiment concluded that adding attention layers at the above-mentioned positions had the most significant effect.

Attention-SolarNet model formula summary:

$$Y = \sigma(W_6 \cdot ReLU(W_5 \cdot Flatten(Dropout(Att(F_4(P_3)))) + b_5) + b_6) \qquad (11)$$

Where:

b_5 for the 512-unit dense layer bias.

b_6 for the final classification bias.

Components:

1. Convolutional Blocks ($i = 1 \; to \; 4$):

$$F_i = ReLU(W_i * P_{i-1} + b_i) \tag{12}$$

where $P_0 = X\ (input\ image)$

2. Pooling:

$$P_i = MaxPool_{ki} \times {}_{ki}(F_i), k_1 = 4, k_2 = k_3 = k_4 = 2 \tag{13}$$

3. Attention Mechanism:

$$Att(X) = X \odot softmax(tanh(X\_flat \cdot W_a + b_a)) \tag{14}$$

where:

X_flat (flattened 12×12→144)

$W_a \in \mathbb{R}^{2\ 50} \times {}^1, b_a \in \mathbb{R}^{1\ 44} \times {}^1$

4. Dropout:

$$Dropout(x) = \{\, x/0.5\ (prob = 0.5), 0\ (otherwise) \,\} \tag{15}$$

5. Classification:

$$Y = \sigma(W_6 D_1 + b_6) \tag{16}$$

Key Symbols:

- $\boldsymbol{\sigma}$: Sigmoid
- $*$: Convolution
- $\odot$: Elementwise multiply
- $\mathbb{R}$: Real-number space

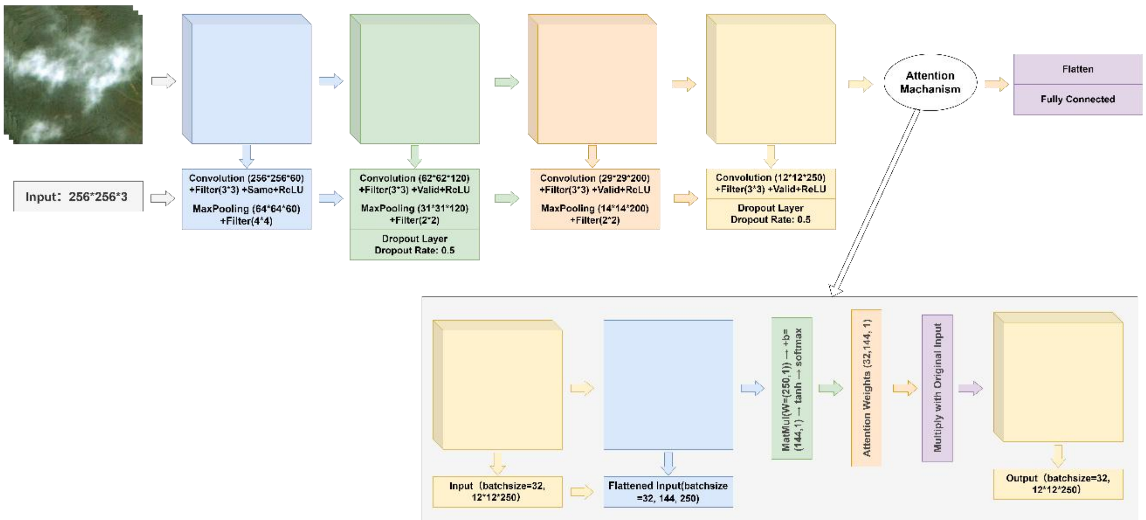


Figure 11: Attention-SolarNet Model for Cloud Detection

The Attention-SolarNet maintained identical training parameters for direct comparability, including the RMSprop optimizer (1e-4 learning rate), batch size (32), and 30-epoch duration. It shared the same loss function (binary crossentropy) and evaluation metrics, emphasizing consistency in performance measurement. The attention mechanism's additional parameters (394 weights) were trained within this framework, with gradients flowing through both the attention layer and convolutional backbone. Identical steps_per_epoch calculation and shuffling protocols were applied, and the same test set assessed improvements attributable to attention. This parity in hyperparameters isolated the attention mechanism's impact, demonstrating its utility through enhanced metric scores rather than training advantages. Both models' reproducibility was ensured by fixed random seeds in data splitting and weight initialization.

The training parameter data of Attention-SolarNet is shown in Table3 as follows:

Total params:	**19,166,337**
Trainable params:	**19,166,337**
Non-trainable params:	**0**

Table 3: Attention-SolarNet Model Summary

This Attention-SolarNet architecture combines the strengths of SolarNet in extracting hierarchical features from images with the attention mechanism to focus on relevant parts of the image, making it particularly effective for tasks requiring fine-grained analysis.

3.3 Dataset

To train this CNN I have used a database with more than 31,500 images from 45 classes and have variety to weather, location and distance. This dataset, created by Northwestern Polytechnical University (NWPU), is a significant contribution to the field, addressing the limitations of previous datasets by offering a large-scale, diverse, and high-quality collection of images. With 31,500 images spanning 45 distinct scene classes, each class represented by 700 images, the NWPU-RESISC45 dataset is not only extensive in scope but also rich in variation. It captures a wide range of factors including translation, spatial resolution, viewpoint, object pose, illumination, background, and occlusion, which are crucial for training robust deep learning models.

The high within-class diversity and between-class similarity of the NWPU-RESISC45 dataset present a formidable challenge for classification algorithms, pushing the boundaries of what is achievable in remote sensing image analysis. This dataset is designed to facilitate the development and rigorous evaluation of data-driven algorithms, particularly those based on deep learning. By providing a common ground for comparison, it enables researchers to assess the performance of various methods and identify areas for improvement. The evaluation of several representative methods using this dataset serves as a valuable baseline, setting a standard for future research and innovation in the field of remote sensing image scene classification. The NWPU-RESISC45 dataset is a testament to the progress made in this domain and will undoubtedly be a catalyst for further advancements.

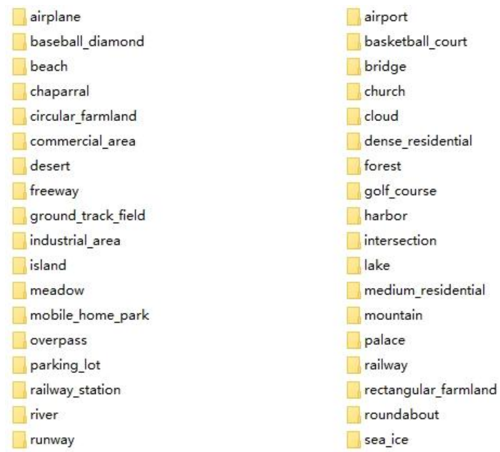


Figure 12: Dataset Structure

3.3.1 Data Split

In my project, the dataset is meticulously divided into training, testing, and validation sets with ratios of 78.23%, 9.04%, and 12.72%, respectively. This partitioning ensures that the model learns on different data during training, evaluation, and testing, thereby enhancing its generalization capabilities and predictive accuracy. Specifically, the training set comprises 1427 images, with cloud images accounting for 37.49%; the validation set includes 232 images, with cloud images making up 31.46%; and the test set contains 165 images, where cloud images constitute 55.75%. The varying proportions of cloud images in each dataset help the model learn to recognize cloud images under different conditions, increasing the model's robustness.

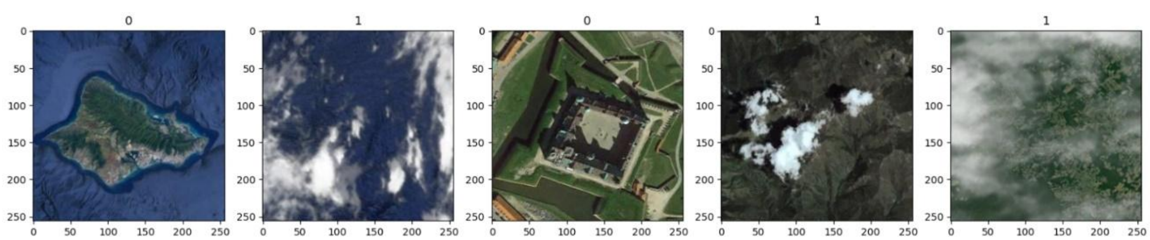


Figure 13: Train Dataset Sample

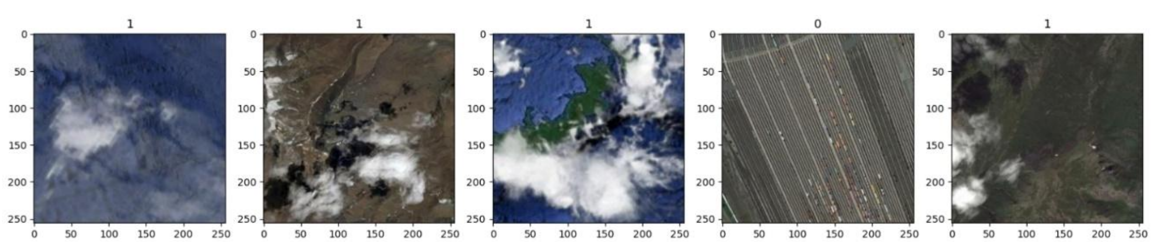


Figure 14: Test Dataset Sample

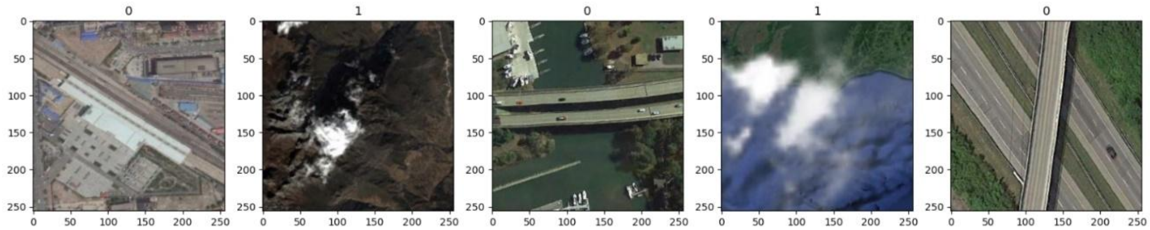


Figure 15: Validation Dataset Sample

3.3.2 Data Balancing

To address the imbalance in the dataset, a function named filter proportion is employed. This function randomly selects a certain proportion of clear-sky images based on the acceptance ratio rat_acept, while retaining all cloudy images. This approach helps to adjust the ratio of cloudy to clear-sky images within the dataset, preventing the model from being biased towards the majority class.

3.3.3 Data Normalization

In the final stage of data preprocessing, the pixel values of the validation set valIm, training set entrIm, and test set testIm are normalized by dividing them by 255. This step transforms the pixel value range from [0, 255] to [0, 1], which is more suitable for model training.

3.3.4 Data Augmentation

The training data is augmented using the ImageDataGenerator class, which introduces random rotations (20 degrees), horizontal and vertical shifts (20% of width and height), shear (20%), zoom (20%), and horizontal flips. The fill_mode='nearest' parameter is used to fill in any newly created pixels. These augmentation techniques help improve the model's generalization capabilities.

3.4 Evaluation Metrics

To evaluate model performance, metrics like accuracy, precision, recall, and F1-score are essential:

- **Accuracy:**

$$\text{Accuracy} = \frac{\text{True Positives + True Negatives}}{\text{Total Sample}} (17)$$

- **Precision (for class c):** This is the criteria that shows the proportion of images that are positively classified as positive

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives + False Positives}} (18)$$

- **Recall (for class c):** This is the criteria that displays the proportion positively identified as positive samples among the actual positive samples.

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives + False Negatives}} (19)$$

- **F1-score (harmonic mean of precision and recall):** F1-Score measures the performance of model by calculating the harmonic mean of Precision and Recall.

$$\text{F1-score} = 2 \cdot \frac{\text{Precision} \times \text{Recall}}{\text{Precision + Recall}} (20)$$

- **Loss:** This criterion measures the cap between results of prediction labels and actual labels. Below shows Equation (9) for classification.

$$Loss \ = \ \sum_{c=1}^{M} y_{ic} \, log(p_{ic}) (21)$$

- **Confusion Matrix:** It displays the accurate number of the True Positive, True Negative, False Positive and False Negative.
- **ROC:** Receiver Operating Characteristic (ROC), which displays the trade-off relationships between the True Positive Rate (also known as sensitivity or recall) and the False Positive Rate of a model at different thresholds.
- **AUC:** Area Under the ROC curve, which demonstrates the overall ability to distinguish between positive and negative samples. In the classification circumstance, AUC acts as metric to evaluate the performance of models for both classes. Generally speaking, a model is considered well performed when the curve rises towards the upper-left corner of the graph, and therefore, leaving more space to AUC. In a nutshell, the closer AUC gets to 1, the better the model is.

These metrics help assess how well the model distinguishes different cloud types, which is crucial for reliable solar irradiance forecasting.

By following this detailed testing and evaluation plan, the project aims to ensure the highest quality of the SolarNet and Attention-SolarNet models, their components, and the overall data processing pipeline. This rigorous approach will contribute to the development of a reliable and efficient system for cloud detection and classification, ultimately optimizing solar energy production.

3.5 Experimental Setup and Technology

The technology this project will be using is displayed in Table 4.

Software	Framework	Tensorflow
	Language	Python
	Libraries	Numpy, Keras, Matplolib, flask
Hardware	Central processing unit (CPU)	13th Gen Intel(R) Core (TM) i7-13620H 2.4GHz
	Graphic processing unit (GPU)	NVIDIA GeForce RTX 4060 8GB

Table 4: Summary of Relevant Technology involved in this project

CUDA version: 11.2.0. cuDNN version: 8.1.0

4 Chapter 4 Experiment and Result Analyses

4.1 Experiment Phases

1. Design and test SolarNet model.
2. Select the best SolarNet model. And design Attention Layer.
3. Testing Attention Layer in different places of the SolarNet model.
4. Select the best Attention-SolarNet model.
5. Fine tune the models to achieve a better result.

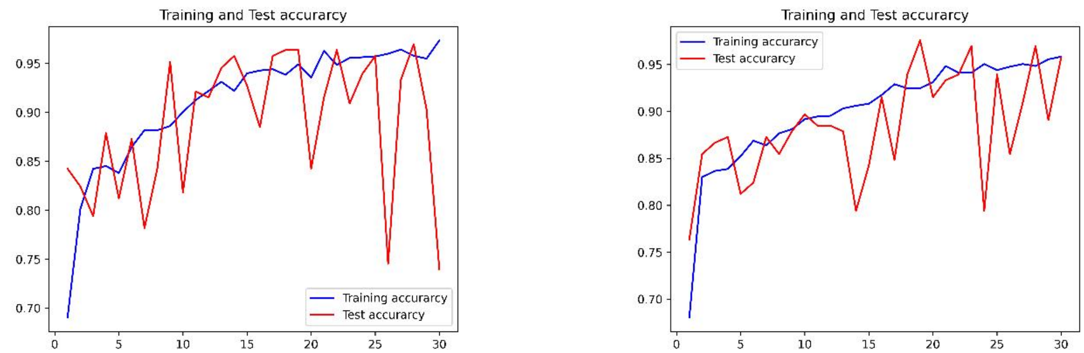
4.2 SolarNet and Attention-SolarNet Experiment Results

The performance is assessed using metrics such as accuracy, precision, recall, and the F1 score. Additionally, a confusion matrix is generated to evaluate the model's class-wise performance, ensuring balanced performance across various cloud types.

4.2.1 Results and Discussion

4.2.1.1 Training and Test Accuracy

Accuracy reflects the model's ability to correctly classify samples. The Attention-SolarNet demonstrates faster accuracy convergence and reduced volatility in test accuracy, indicating better generalization. This stability suggests that the attention mechanism acts as a form of implicit regularization, preventing overfitting and enhancing robustness. In solar energy applications, where models must perform accurately across a wide range of image conditions and sources, from ground-based photography to satellite imagery, the Attention-SolarNet 's consistent accuracy ensures reliable cloud detection support for power forecasting, storage management, and grid integration, even when faced with varying environmental conditions and data sources.



a) Train acc=97.35%, Test acc=73.94% b) Train acc=95.84%, Test acc=95.76%

Figure 16: a) and b) demonstrate the SolarNet and Attention-SolarNet model accuracy

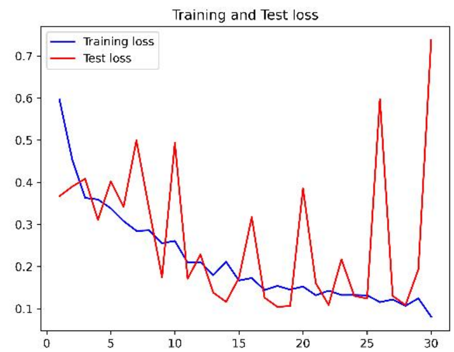
Data Analysis:

- **SolarNet**: Training accuracy=0.9735, Test accuracy=0.7394. The SolarNet model achieves high training accuracy but shows significant volatility in test accuracy, indicating potential overfitting to the training data. This can be a concern in solar energy applications where the model must generalize well to unseen images from diverse sources and environmental conditions, such as varying weather patterns, geographic locations, and image acquisition platforms, to provide consistent and accurate cloud detection for power forecasting and grid management.

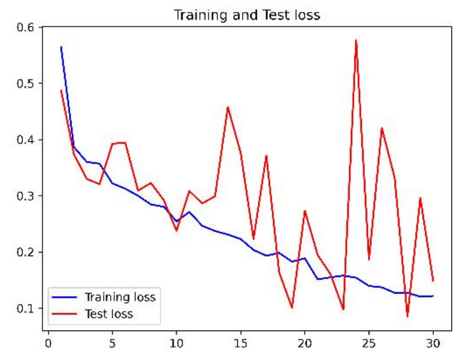
- **Attention-SolarNet**: Training accuracy=0.9584, Test accuracy=0.9576. The Attention-SolarNet model demonstrates consistent accuracy between training and testing phases, with minimal volatility. This indicates better generalization and robustness, making it more reliable for real-world solar energy applications where the model must maintain high accuracy across a wide range of image conditions and sources, ensuring effective power forecasting, storage optimization, and grid stability support under varying operational scenarios.

4.2.1.2 Training and Test Loss

Loss measures the model's prediction error. The Attention-SolarNet's faster loss reduction and smoother training dynamics highlight its efficiency in optimizing feature representations. This efficiency translates to quicker learning, making Attention-SolarNet more practical for real-time applications in solar energy, such as dynamic power forecasting systems or smart grid integration platforms, where rapid deployment and on-the-fly adjustments are necessary to respond to changing cloud conditions and environmental factors, ensuring optimal power generation and distribution.



a) Train loss=8.11%, Test loss=73.72%



b) Train loss=12.17%, Test loss=14.89%

Figure 17: a) and b) demonstrate the SolarNet and Attention-SolarNet model loss

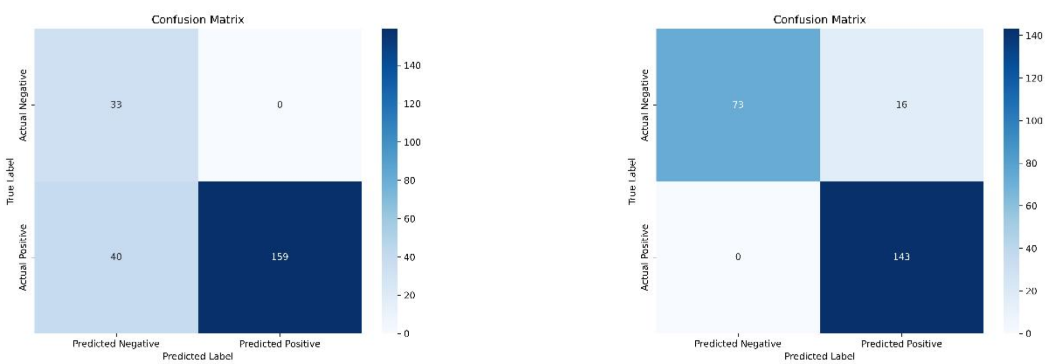
Data Analysis:

- **SolarNet**: Training loss=0.0811, Test loss=0.7372. The SolarNet model shows a significant gap between training and test loss, indicating potential overfitting to the training data. Higher test loss suggests that the model does not generalize well to unseen images, which can be a critical issue in solar energy applications where the model must maintain accuracy across varying image conditions and data sources to support effective power forecasting, storage management, and grid integration.

- **Attention-SolarNet**: Training loss=0.1217, Test loss=0.1489. The Attention-SolarNet model demonstrates a smaller gap between training and test loss, indicating better generalization. The smoother reduction in loss over training epochs highlights the efficiency of the attention mechanism in optimizing feature representations, ensuring that the model can quickly adapt to new data and maintain high accuracy in cloud detection tasks across different operational scenarios and image sources, providing reliable support for solar energy systems to optimize power generation, storage, and grid interactions.

4.2.1.3 Confusion Matrix

The confusion matrix is a fundamental tool for evaluating classification models. For the SolarNet model, the high FN rate (40) indicates a critical weakness in identifying cloud images, which can lead to underestimated solar irradiance and suboptimal energy forecasts. This weakness may stem from the model's inability to focus on discriminative features of cloud formations, resulting in missed detections that could affect the efficiency of solar power generation and grid management. In contrast, the Attention-SolarNet model achieves FN=0, demonstrating perfect recall. This is particularly significant in solar energy applications, where accurate cloud detection is essential for predicting power output and optimizing energy storage and distribution. The Attention-SolarNet's slight increase in FP (16) is a deliberate trade-off to prioritize recall, ensuring that solar energy systems can proactively adjust to impending cloud cover and maintain optimal performance.



a) SolarNet model confusion matrix

b) Attention-SolarNet model confusion matrix

Figure 18: a) and b) demonstrate the SolarNet and Attention-SolarNet model confusion matrix

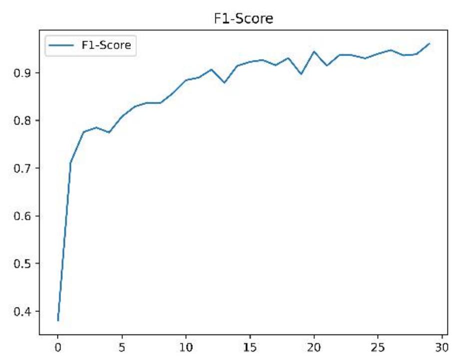
Data Analysis:

- **SolarNet**: TN=33, FP=0, FN=40, TP=159. The high FN rate suggests that the SolarNet model is not effective in identifying cloud images, which could lead to significant inaccuracies in solar power forecasting and affect the reliability of energy supply.
- **Attention-SolarNet**: TN=73, FP=16, FN=0, TP=143. The perfect recall (FN=0)

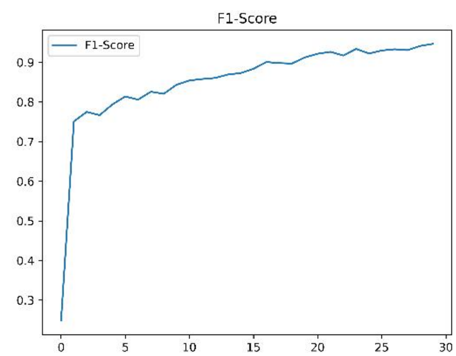
indicates that the Attention-SolarNet model is highly effective in identifying cloud images, providing solar energy systems with the accurate and timely data needed to optimize power generation and storage strategies.

4.2.1.4 F1-Score

The F1-score provides a harmonic means of precision and recall, offering a holistic view of model performance. The SolarNet model's F1-score improves steadily, reflecting gradual learning. However, the slower convergence suggests that the model requires more data or longer training to optimize feature selection, which may not be feasible in dynamic solar energy environments where rapid adaptation to changing weather conditions is necessary. In contrast, the Attention-SolarNet's F1-score rises faster, indicating that the attention mechanism accelerates learning by directing focus to salient features of cloud formations. This efficiency is particularly valuable in solar energy applications, where quick and accurate cloud detection can significantly enhance the precision of power output predictions and support more effective grid integration and management.



a) SolarNet model F1-Score=0.9605



b) Attention-SolarNet model F1-Score=0.9467

Figure 19: a) and b) demonstrate the SolarNet and Attention-SolarNet model F1-Score

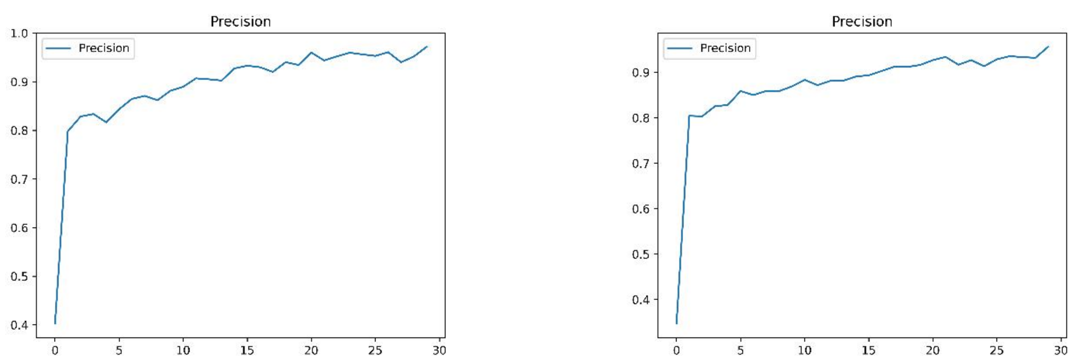
Data Analysis:

- **SolarNet**: F1-score=0.9605. The steady improvement indicates that the SolarNet model learns effectively over time, but the slower convergence suggests that it may not adapt quickly enough to the rapidly changing weather conditions typical in solar energy environments, potentially leading to less accurate power forecasts.

- **Attention-SolarNet**: F1-score=0.9467. The faster convergence of the F1-score for the Attention-SolarNet model highlights the efficiency of the attention mechanism in optimizing feature selection, enabling quicker learning and better performance in fewer training epochs. This rapid adaptation is crucial for solar energy systems that need to respond promptly to weather changes to maintain optimal power generation and grid stability.

4.2.1.5 Precision

Precision measures the accuracy of positive predictions and is critical in solar energy applications where false positives can lead to unnecessary adjustments in power generation and storage systems, increasing operational costs and reducing overall efficiency. Both models achieve comparable precision, but the Attention-SolarNet stabilizes faster. This stability can be attributed to the attention mechanism's ability to suppress noise and irrelevant information, such as non-cloud aerial features, leading to more consistent predictions that support reliable decision-making in solar energy management.



a) SolarNet model precision=0.9718

b) Attention-SolarNet model precision=0.9562

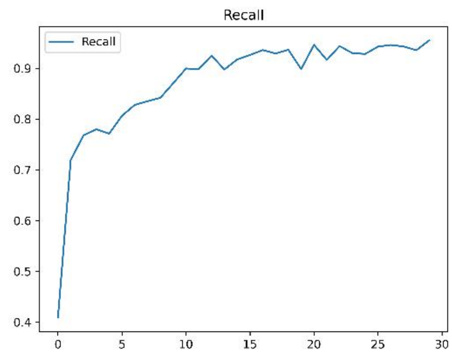
Figure 20: a) and b) demonstrate the CNN and Attention-SolarNet model precision

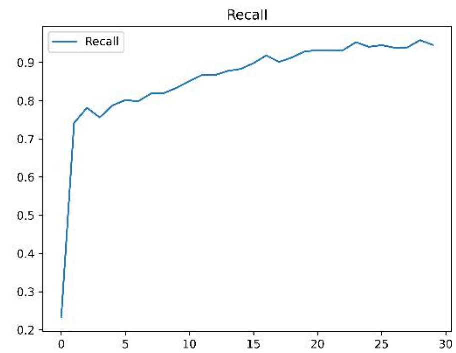
Data Analysis:

- **SolarNet**: Precision=0.9718. The SolarNet model demonstrates high precision, indicating that when it predicts a cloud image, it is very likely to be correct. However, the precision metric alone does not account for the high FN rate, which can result in missed opportunities to optimize power output and storage in response to actual cloud cover.
- **Attention-SolarNet**: Precision=0.9562. The Attention-SolarNet model also achieves high precision, with a slight trade-off due to the increased FP rate. Despite this, the Attention-SolarNet's precision is still sufficiently high for solar energy applications, especially considering its superior recall and the critical need for comprehensive cloud data to ensure efficient and reliable power generation and grid support.

4.2.1.6 Recall

Recall measures the model's ability to identify positive samples and is paramount in solar energy applications, where missing cloud detections can result in inaccurate power forecasts and inefficient energy storage and distribution strategies. The SolarNet model's recall improves but remains hindered by a high FN rate, suggesting that SolarNet may struggle with the complex and varied features of cloud images, particularly when dealing with different cloud types and densities that are common in solar energy environments. The Attention-SolarNet's perfect recall (FN=0) underscores the power of attention mechanisms in enhancing feature discrimination, ensuring that cloud images are prioritized and accurately detected, even in challenging conditions with varying cloud formations. This capability is essential for solar energy systems to make precise and timely adjustments to power generation and storage, maximizing energy output and grid reliability.





a) SolarNet model recall=0.9549

b) Attention-SolarNet model recall=0.9460

Figure 21: a) and b) demonstrate the SolarNet and Attention-SolarNet model recall

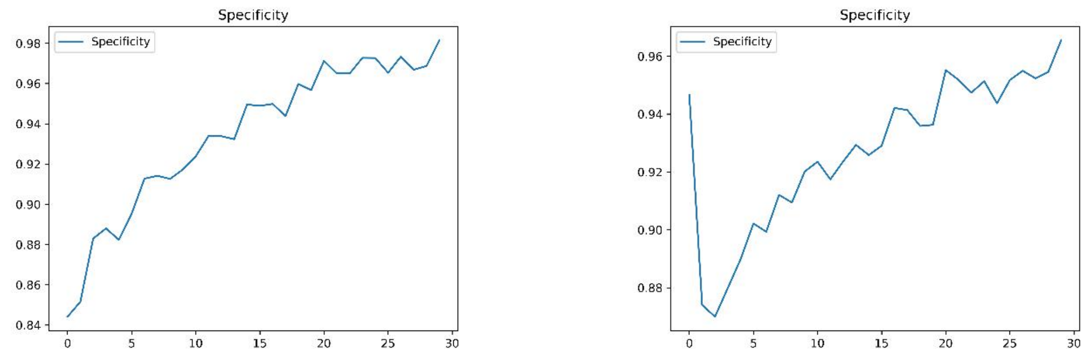
Data Analysis:

- **SolarNet**: Recall=0.9549. While the SolarNet model achieves relatively high recall, the FN rate of 40 indicates that it still misses a significant number of cloud images, which can lead to substantial inaccuracies in solar power forecasting and affect the overall efficiency and economic viability of solar energy projects.

- **Attention-SolarNet**: Recall=0.9460. The Attention-SolarNet model achieves near-perfect recall with FN=0, demonstrating its superior ability to identify cloud images. This ensures that solar energy systems have access to complete and accurate cloud data, enabling them to optimize power generation, storage, and distribution strategies for maximum efficiency and grid support.

4.2.1.7 Specificity

Specificity measures the model's ability to identify negative samples (non-cloud images) and is vital in solar energy applications where false positives can trigger unnecessary adjustments in power generation and storage systems, leading to increased operational costs and reduced system efficiency. While both models improve over time, the Attention-SolarNet achieves higher specificity with faster convergence. This efficiency can be linked to the attention mechanism's role in refining feature representations, enabling clearer separation between cloud and non-cloud images. This capability is crucial for maintaining operational efficiency and accuracy in solar energy systems, ensuring that they can distinguish between actual cloud cover and other aerial features, such as birds or aircraft, to avoid unnecessary operational disruptions and support optimal power generation and grid support.



a) SolarNet model specificity=0.9815 b) Attention-SolarNet model specificity=0.9655

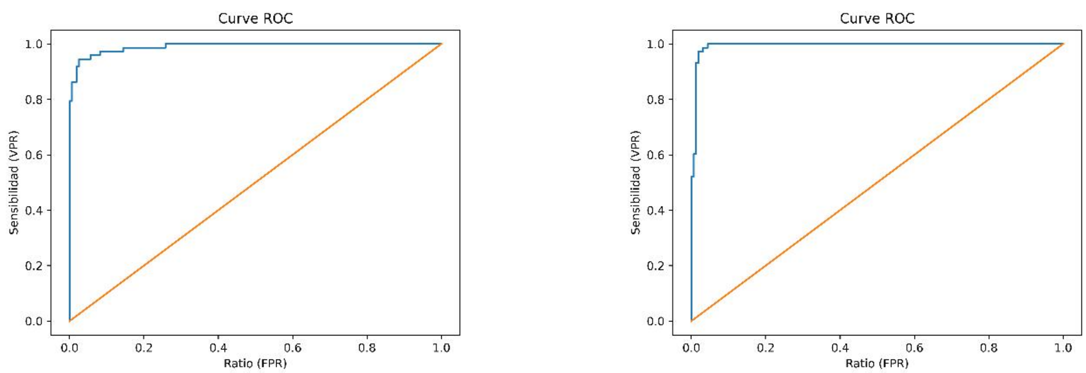
Figure 22: a) and b) demonstrate the SolarNet and Attention-SolarNet model specificity

Data Analysis:

- **SolarNet**: Specificity=0.9815. The SolarNet model demonstrates high specificity, indicating that it is very effective at identifying non-cloud images with minimal false positives. This is important for solar energy applications where clear skies are common, and cloud detection needs to be precise to avoid operational inefficiencies and unnecessary adjustments.
- **Attention-SolarNet**: Specificity=0.9655. The Attention-SolarNet model also achieves high specificity, with a slight trade-off due to the increased FP rate. Despite this, the Attention-SolarNet's specificity is still sufficiently high for solar energy applications, especially considering its superior recall and overall performance in accurately detecting both cloud and non-cloud images. This ensures that solar energy systems can maintain efficient operations with minimal disruptions while effectively responding to actual cloud conditions to optimize power generation and grid reliability.

4.2.1.8 ROC Curve

The ROC curve evaluates a model's ability to distinguish between classes across varying thresholds. The Attention-SolarNet 's curve is closer to the ideal top-left corner, indicating superior performance at all threshold levels. This robustness is essential in solar energy applications, where accurate cloud detection across different thresholds ensures reliable data collection and analysis for power forecasting and grid management. The ability to maintain high performance across varying detection thresholds allows solar energy systems to adapt effectively to changing weather conditions and operational requirements, enhancing overall system reliability and efficiency.



a) SolarNet model ROC curve b) Attention-SolarNet model ROC curve

Figure 23: a) and b) demonstrate the SolarNet and Attention-SolarNet model specificity

Data Analysis:

- **SolarNet**: The ROC curve for the SolarNet model approaches the top-left corner but with room for improvement, indicating good classification performance but with potential for further optimization to enhance cloud detection accuracy across various operational conditions and cloud types encountered in solar energy settings.

- **Attention-SolarNet**: The ROC curve for the Attention-SolarNet model is closer to the ideal top-left corner, reflecting better discrimination between cloud and non-cloud images at all threshold levels. This suggests that the Attention-SolarNet model is more reliable for solar energy applications, where precise cloud detection across different thresholds is necessary to support accurate power forecasting, efficient energy storage management, and stable grid integration.

Table 5 shows the summary of the SolarNet and Attention-SolarNet Experiment Results.

	SolarNet	Attention- SolarNet
Training Loss:	**8.11%**	12.17%
Training Accuracy:	**97.35%**	95.84%
Test Loss:	73.72%	**14.89%**
Test Accuracy:	73.94%	**95.76%**
Validation Loss:	47.62%	**22.87%**
Validation Accuracy:	82.75%	**93.10%**
Specificity:	**98.15%**	96.55%
Precision:	**97.18%**	95.62%
Recall:	**95.49%**	94.60%
F1-Score	**96.05%**	94.67%
Test Specificity	**100.00%**	87.37%
Test Precision	**100.00%**	89.38%
Test Recall	52.73%	**100.00%**
Test F1-Score	68.90%	**94.00%**

Table 5: SolarNet and Attention-SolarNet Model Result

4.3 Model Comparison

The experimental results highlight the superior performance of Attention-SolarNet for cloud detection in solar energy applications. While pretrained models like ResNet101 and ResNet50 achieve near-perfect training accuracy (99.96% and 99.77%, respectively) and low training loss (0.34–0.44%), they catastrophically fail on real-world test data, yielding 0% precision and recall due to severe overfitting. In contrast, Attention-SolarNet delivers exceptional generalization, achieving the highest test accuracy (95.76%) and validation accuracy (93.10%) across all models, coupled with the lowest test loss (14.89%) and validation loss (22.87%). Its balanced precision-recall tradeoff (Test F1-score: 94.00%, Test Precision: 89.38%, Test Recall: 100%) ensures reliable detection of clouds without critical misses—a stark improvement over SolarNet's 52.73% test recall and EfficientNet's 83.17%, which risk overlooking clouds that impact energy output. Furthermore, Attention-SolarNet avoids the extreme specificity imbalances seen in other models (e.g., SolarNet's 100% test specificity but poor recall, or ResNet101's 0%

specificity), maintaining practical robustness with 87.37% test specificity. This performance stems from its attention mechanism, which likely focuses on discriminative cloud features while suppressing irrelevant background noise, enabling adaptability to complex sky conditions like haze or partial cloud cover. By combining high generalizability, avoidance of catastrophic failure scenarios, and optimal recall-precision balance, Attention-SolarNet emerges as the most reliable choice for solar energy systems, where accurate cloud detection directly translates to efficient power generation under diverse environmental conditions.

Table 6 shows the summary of the SolarNet, Attention-SolarNet and other 3 Pre-Train Model Experiment Results.

	SolarNet	Attention-SolarNet	ResNet50	ResNet101	EfficientNet
Training Loss:	8.11%	12.17%	0.44%	**0.34%**	1.02%
Training Accuracy:	97.35%	95.84%	99.77%	**99.96%**	99.75%
Test Loss:	73.72%	**14.89%**	93.34%	617.96%	67.36%
Test Accuracy:	73.94%	**95.76%**	41.28%	41.28%	62.79%
Validation Loss:	47.62%	22.87%	57.47%	**352.46**%	67.24%
Validation	82.75%	**93.10%**	66.13%	66.13%	47.41%
Specificity:	98.15%	96.55%	99.96%	**100.00%**	99.99%
Precision:	97.18%	95.62%	99.75%	**99.89%**	99.53%
Recall:	95.49%	94.60%	99.61%	**100.00%**	99.79%
F1-Score	96.05%	94.67%	99.68%	**99.95%**	99.66%
Test Specificity	**100.00%**	87.37%	78.87%	0.00%	67.61%
Test Precision	**100.00%**	89.38%	0.00%	0.00%	64.12%
Test Recall	52.73%	**100.00%**	0.00%	0.00%	83.17%
Test F1-Score	68.90%	**94.00%**	0.00%	0.00%	72.41%

Table 6: SolarNet, Attention-SolarNet and other 3 Pre-Train Model Results

4.4 Model Visualization

Grad-CAM is a technique that visualizes Convolutional Neural Network by highlighting localizations in images which enhances the interpretability of the model and extracts important variables [22]. How it works is that the bluer the area is, the more focus the model is.

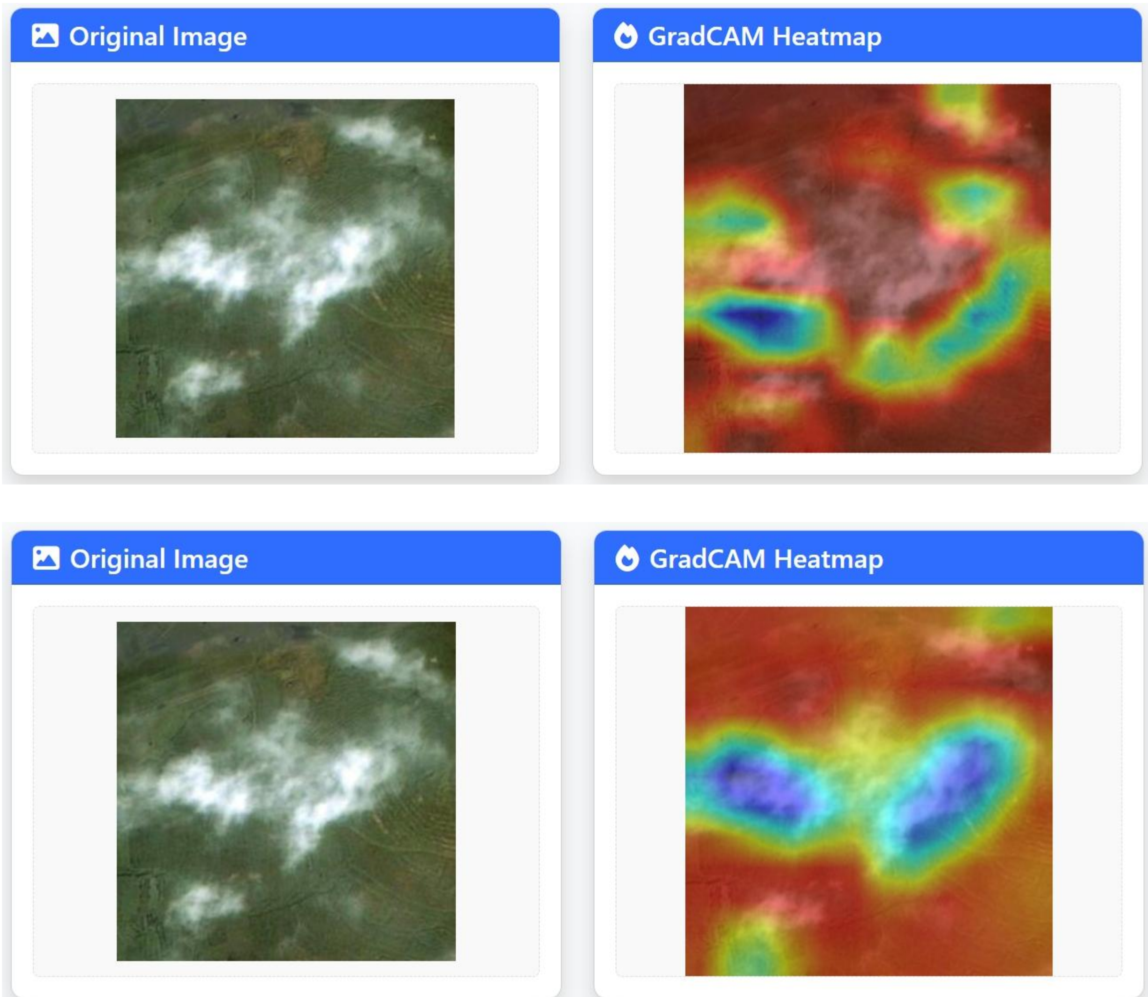


Figure 24: SolarNet and Attention-SolarNet Grad-CAM Visualization

4.5 Model Deployment

The homepage of the cloud detection system is shown in Figure 25.

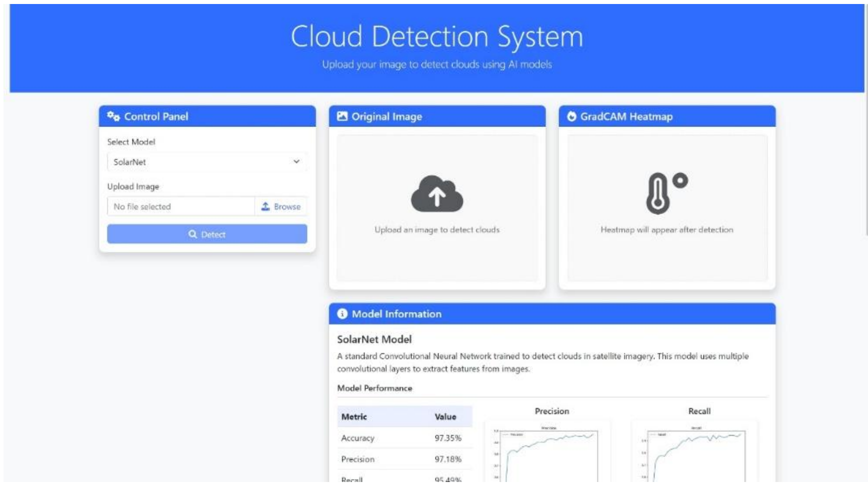


Figure 25: Website homepage

As shown in figure 26, when users click the browse button, they will enter such an image selection interface.

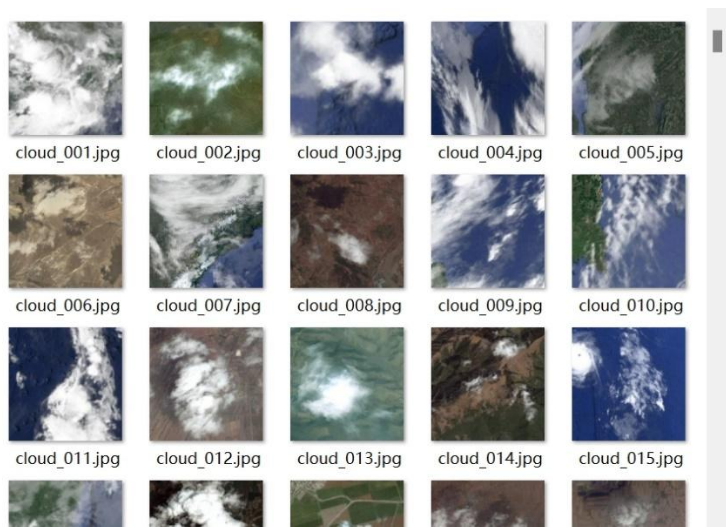


Figure 26: Image upload GUI

As shown in figure 27, it is the interface after the user uploads the image to be checked by the SolarNet model

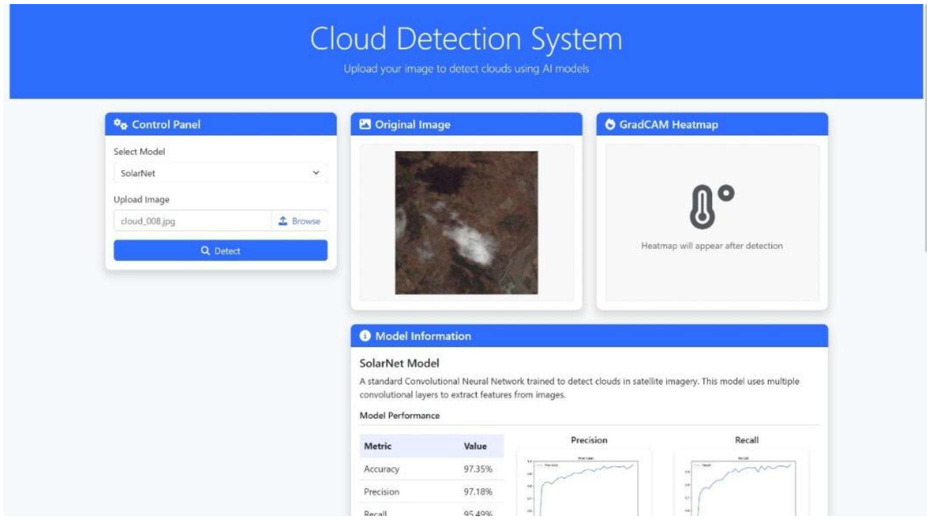


Figure 27: Upload image for SolarNet model

As shown in figure 28, it is the result display after SolarNet detects the image.

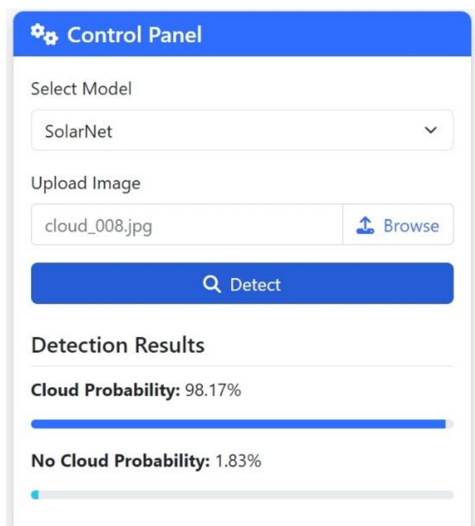


Figure 28: SolarNet control panel

As shown in figure 29, it is the result and Grab-CAM display after SolarNet detects the image.

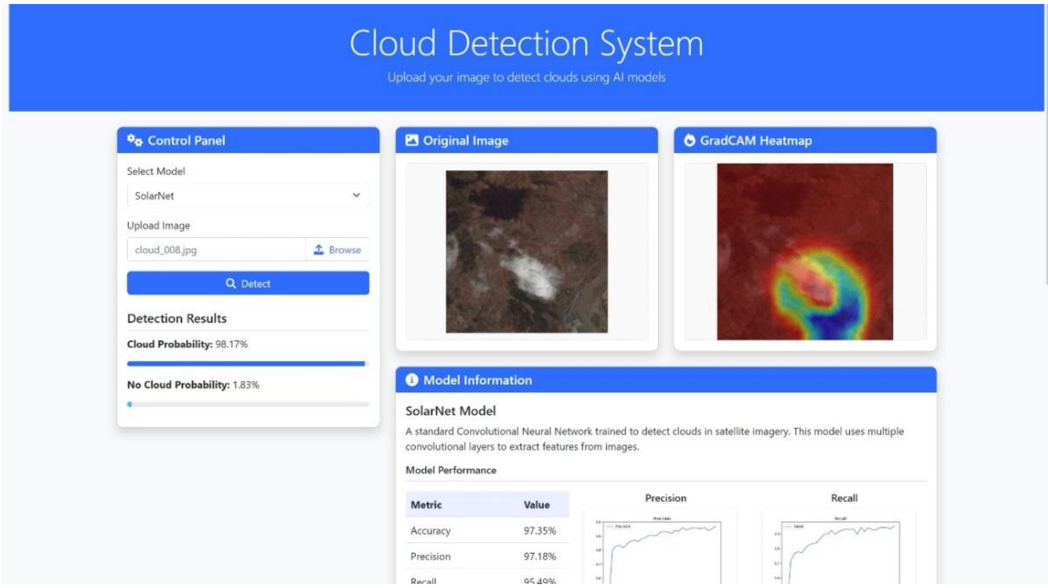


Figure 29: SolarNet detection result

As shown in figure 30, it is the SolarNet model information.

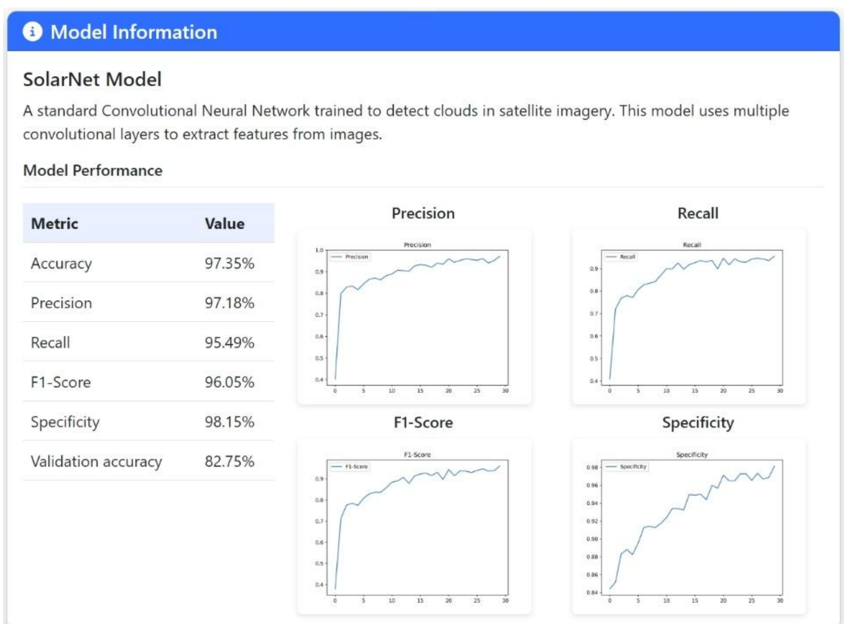


Figure 30: SolarNet model information

As shown in figure 31, it is the interface after the user uploads the image to be checked by the Attention-SolarNet model.

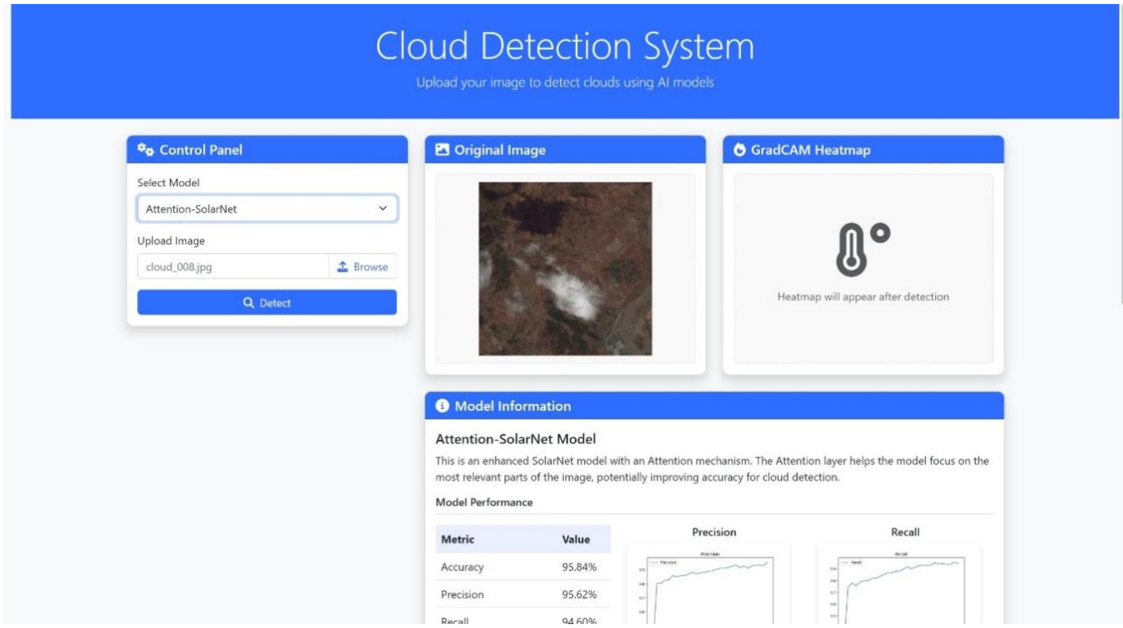


Figure 31: Upload image for Attention-SolarNet model

As shown in figure 32, it is the result display after Attention-SolarNet detects the image.

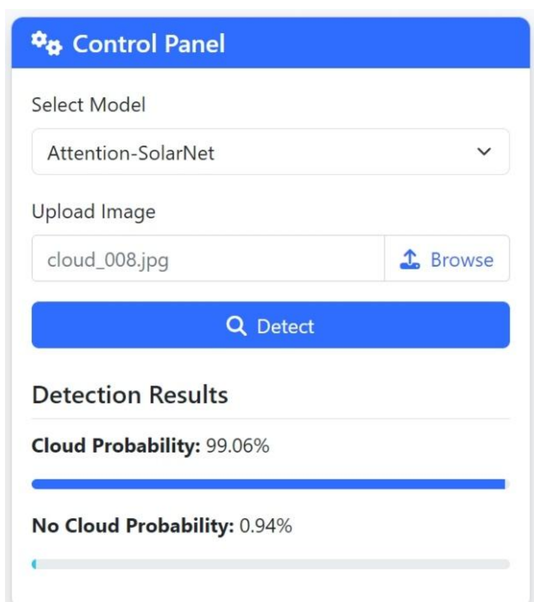


Figure 32: Attention-SolarNet control Panel

As shown in figure 33, it is the result and Grab-CAM display after Attention-SolarNet detects the image.

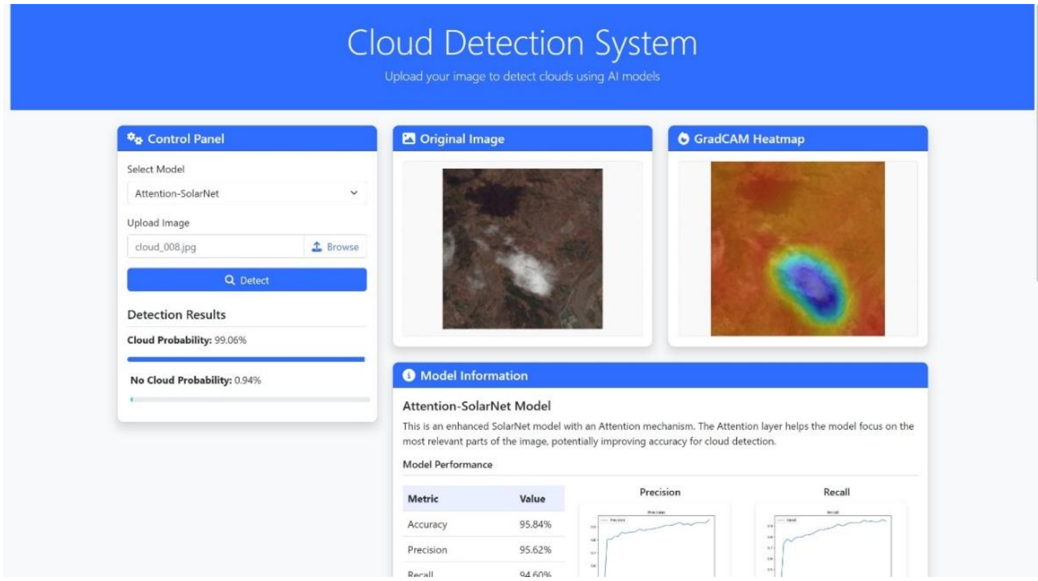


Figure 33: Attention-SolarNet detection result

As shown in figure 34, it is the Attention-SolarNet model information.

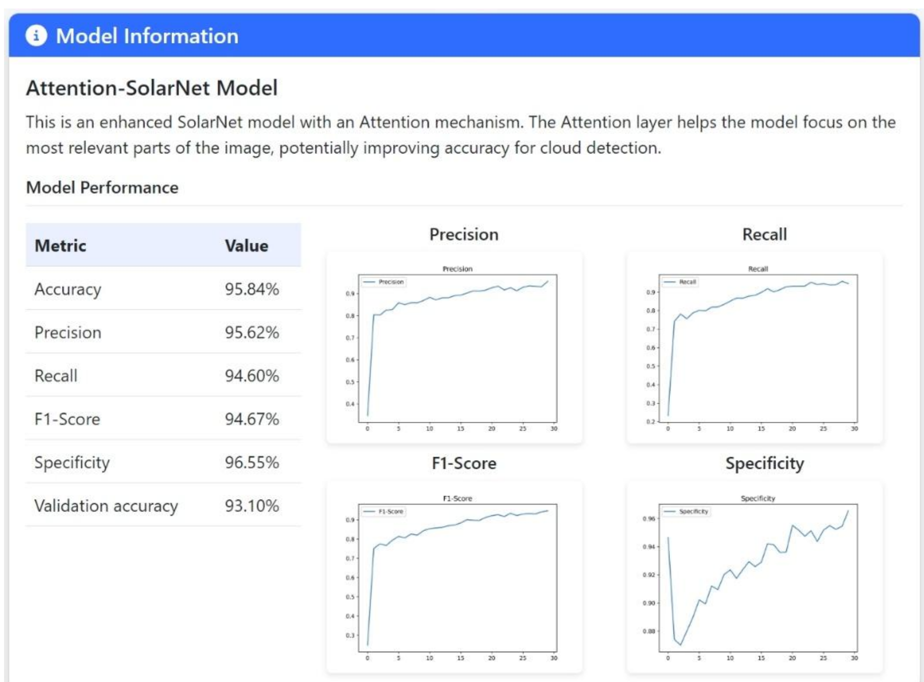
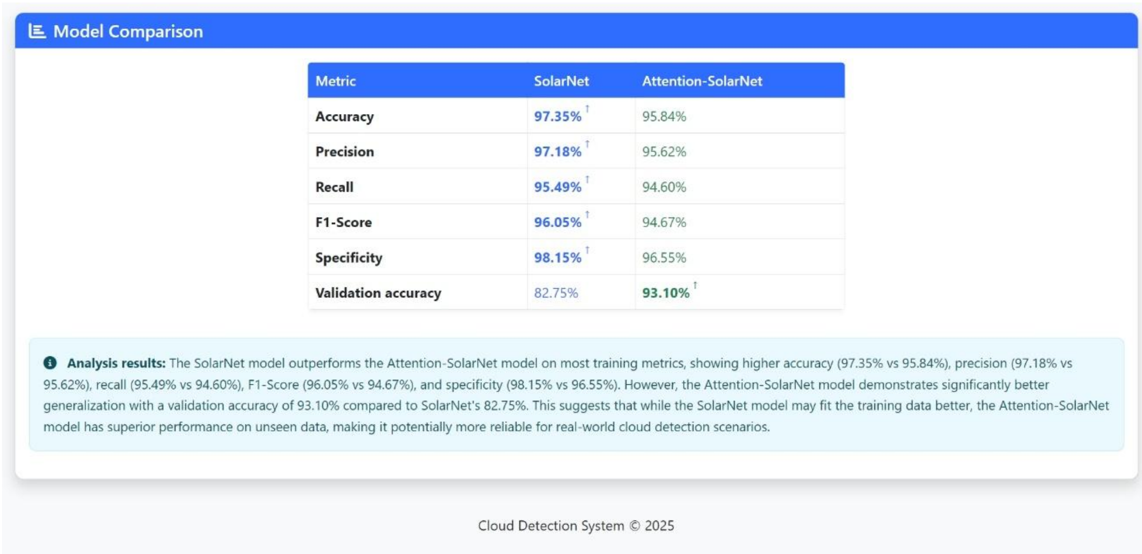


Figure 34: Attention-SolarNet model information

As shown in figure 35, it is the SolarNet and Attention-SolarNet model comparison.



Model Comparison

Metric	SolarNet	Attention-SolarNet
Accuracy	**97.35%** ↑	95.84%
Precision	**97.18%** ↑	95.62%
Recall	**95.49%** ↑	94.60%
F1-Score	**96.05%** ↑	94.67%
Specificity	**98.15%** ↑	96.55%
Validation accuracy	82.75%	**93.10%** ↑

Analysis results: The SolarNet model outperforms the Attention-SolarNet model on most training metrics, showing higher accuracy (97.35% vs 95.84%), precision (97.18% vs 95.62%), recall (95.49% vs 94.60%), F1-Score (96.05% vs 94.67%), and specificity (98.15% vs 96.55%). However, the Attention-SolarNet model demonstrates significantly better generalization with a validation accuracy of 93.10% compared to SolarNet's 82.75%. This suggests that while the SolarNet model may fit the training data better, the Attention-SolarNet model has superior performance on unseen data, making it potentially more reliable for real-world cloud detection scenarios.

Cloud Detection System © 2025

Figure 35: SolarNet and Attention-SolarNet model comparison

5 Chapter 5 Project Management

5.1 Activities

Table 7: Activities of the Project

Phase	Task	Status
1-1	Conduct could detection and classification research	Complete
1-2	Identify and narrow issues	Complete
1-3	Dig into solutions of deep learning method for could detection	Complete
1-4	Study classification methods and models	Complete
2-1	Research on could detection and classification specifically in CNNs	Complete
2-2	Study ten CNN models and relevant programming methods	Complete
2-3	Understand evaluation methods of CNNs	Complete
2-4	Investigate attention mechanisms to improve models and performances	Complete
3-1	Gather 1 to 3 datasets from Kaggle, Github and NASA, and select one suitable dataset	Complete
3-2	Complete basic data separation and preprocessing	Complete
3-3	Test processed dataset	Complete
4-1	Design SolarNet models. Train and test the processed data on SolarNet models	Complete
4-2	Design and train the Attention-SolarNet model on the dataset	Complete
4-3	Optimized attention mechanisms based on the training results	Complete
4-4	Sort out the experiments process and start fine-tuning	Complete
5-1	Compare the Attention-SolarNet model with SolarNet model and 3 pre-train models	Complete
5-2	Deploy the model with website application	Complete
5-3	Finish the final report, deployment and presentation preparation	Complete

5.1.1 Schedule

The schedule is shown in table 8.

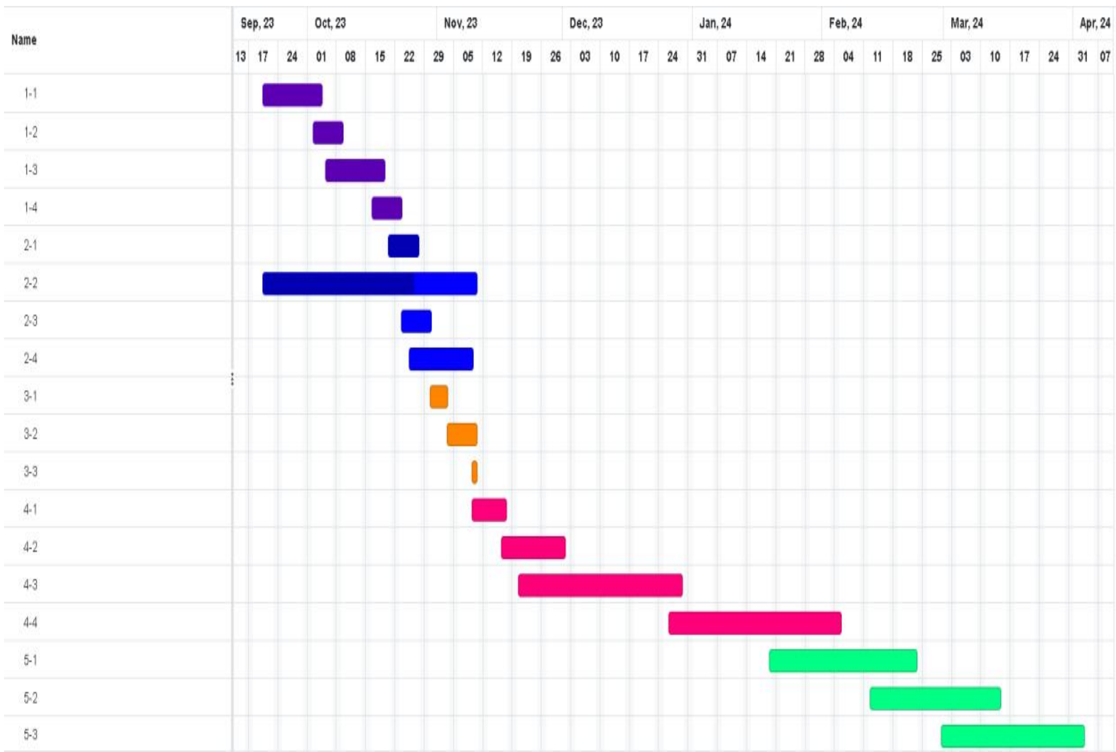


Table 8: Gantt Chart

5.1.2 Project Version Management

GitHub: https://github.com/Jasckii/CouldDetection

5.1.3 Project Data Management

A. All files including datasets, model codes, references, weekly reports and all sorts will be replicated into three copies for fail safe, one on local computer, one on hard drive, one on GitHub

B. Upload the project to GitHub for every modification, synchronize the project on three platforms

The following are documents of the Project for uploading and synchronization:

1. Reports (Weekly, Proposal, Progress, Final) & Presentation PPT

2. SolarNet model and Attention-SolarNet model diagram

3. References
4. Datasets Link: https://arxiv.org/abs/1703.00121
5. Model evaluation documents
6. Model codes (Different versions)

5.1.4 Deliverables

1. The project proposal
2. Progress Report
3. Final Project Report
4. Project codes
5. Project presentation slides

5.2 Risk Analysis

Risk analysis is a critical component of project management, and for this project several potential risks have been identified and are being actively managed. Here is the analysis based on the current project progress:

Resolved Risks and Mitigation Success:

- **Data Availability and Quality:** Initially, there was a risk of insufficient or low-quality data, which could have hampered the training of the model. This risk was mitigated by sourcing a comprehensive database with over 31,500 images from 45 classes, ensuring a diverse and robust dataset for model training.
- **Model Accuracy:** The risk of the model not achieving the desired level of accuracy was addressed by incorporating advanced deep learning techniques and continuous hyperparameter tuning. Early model evaluations indicate a high success rate in cloud detection and classification.
- **Technology Failures:** The risk of hardware or software failure was mitigated by using reliable technology stacks and having backup systems in place. Regular data backups and version control practices using GitHub have been implemented to prevent data loss.

Changes to Project Plan Due to Risks:

- **Schedule Adjustments:** The project timeline had to be adjusted to accommodate additional time for data preprocessing and model training due to the complexity of the dataset. This was achieved without compromising the project's end goals by optimizing resource allocation and task prioritization.
- **Budget Reallocation:** To address unexpected costs associated with advanced computational resources, the project budget was realigned to prioritize GPU usage and cloud-based storage solutions, ensuring that the model training process was not impeded.

Future Risks:

- **Technological Obsolescence:** As AI and ML technologies evolve rapidly, there is a risk that the chosen frameworks or libraries may become outdated. To mitigate this, the project will maintain a flexible technology stack and plan for regular updates and migrations to newer technologies.
- **Regulatory Changes:** Changes in data privacy laws and regulations could impact the project's data handling practices. The project will stay abreast of legal developments and ensure compliance with all relevant regulations.
- **Environmental Factors:** The project relies on accurate weather data, and unforeseen environmental factors could affect data collection. A risk mitigation strategy includes diversifying data sources and implementing backup data collection methods.
- Table 7 displays the analyzed risks during the project progress.

Table7: Risk Analysis

Risk ID	Potential Risk	Cause ID	Potential Causes	Severity	Likelihood	Risk	Mitigation ID	Mitigation
R 1.1	Loss of Project Data	C 1.1.1	Poor version Control	4	1	4	M1.1.1	Regularly update project to cloud
			Physical Hardware	4	1	4	M1.1.2	Hardware Check &

			Failure					Backup
R 1.2	Memory Leakage	C 1.2.1	Model training exceeds the hardware ability	4	3	12	M1.2.1	Use cloud service
R 1.3	Model training issues	C 1.3.1	Data imbalance	2	4	8	M1.3.1	Designed A Filter Function
		C 1.3.2	Low data quality	4	1	4	M1.3.2	Find trusted source on Github
R 1.4	Software issues	C 1.4.1	Virtual environment error	4	1	4	M1.4.1	Keep Virtual Environment Clean
R 2.1	Miss deadline	C 2.1.1	Illness	3	1	3	M2.1.1	Keep healthy
		C 1.3.2	Poor time management	4	1	4	M2.1.2	Strictly follow a schedule

5.3 Professional Issues

The project "Cloud Detection and Classification in Radiance Sky Images for Solar Energy Optimization Using Attention-SolarNet" raises several professional issues that must be considered in the context of legal, social, ethical, and environmental factors.

Legal Issues:

- **Data Protection:** The project handles a large dataset, which necessitates adherence to data protection laws such as the General Data Protection Regulation (GDPR). Personal data must be anonymized, and data breaches must be managed according to legal requirements.

- **Intellectual Property:** The algorithms developed in this project are subject to intellectual property rights. The project will ensure that all innovations are properly protected and that any third-party IP is respected.

Social Issues:

- **Access to Renewable Energy:** The project aims to optimize solar energy production, which has social implications for energy access and affordability. The outcomes could contribute to more equitable access to clean energy.
- **Employment Impact:** Automation of cloud detection and classification may affect job roles in meteorology and solar energy sectors. The project will consider the impact on employment and suggest upskilling or reskilling initiatives.

Ethical Issues:

- **Transparency and Accountability:** The project will maintain transparency in its methods and results, ensuring that the model's predictions are accountable and can be audited.
- **Bias and Fairness:** Efforts will be made to ensure that the AI model does not perpetuate biases, particularly in its impact on different regions or demographic groups.

Environmental Issues:

- **Carbon Footprint:** The project will assess the carbon footprint of its operations, including the energy consumption of model training, and strive to minimize its environmental impact.
- **Sustainability:** By optimizing solar energy production, the project contributes to sustainability goals by supporting the use of renewable energy and reducing reliance on fossil fuels.

The project is committed to upholding the highest standards of professional conduct and will continuously evaluate and address these issues throughout the project lifecycle.

6 Chapter 6 Conclusion

This project has focused on enhancing solar energy optimization through advanced cloud detection models. Accurate cloud detection is crucial for predicting solar irradiance and improving the efficiency of solar power generation and storage systems. I have developed and evaluated two primary models: a SolarNet and an Attention-SolarNet. The SolarNet model serves as a baseline, featuring multiple convolutional and max-pooling layers, ReLU activation functions, and dropout layers for regularization. It concludes with fully connected layers and a sigmoid output for binary classification. The Attention-SolarNet extends this architecture by incorporating an attention layer, which dynamically assigns weights to different features, allowing the model to focus on critical aspects such as cloud formations while suppressing noise and irrelevant information. Performance evaluation reveals that the SolarNet model demonstrates competent performance in cloud detection, achieving a training accuracy of 97.35% and a test accuracy of 73.94%. However, it exhibits higher test loss (73.72%) and lower test recall (52.73%), indicating limitations in handling complex cloud patterns and varying environmental conditions. The Attention-SolarNet model significantly outperforms the SolarNet with a test accuracy of 95.76% and a substantially lower test loss of 14.89%. It also achieves superior recall (100.00%) and a higher F1-score (94.00%), highlighting its effectiveness in accurately detecting clouds under diverse conditions.

Despite the advantages of the Attention-SolarNet model, several limitations have been identified. The attention mechanism increases computational complexity, as evidenced by higher training loss (12.17%) compared to SolarNet (8.11%), requiring more resources for training and deployment. This could be challenging in resource-constrained environments. The Attention-SolarNet also shows a slight trade-off in precision (95.62% vs. 97.18% in SolarNet) due to increased false positives, although its recall remains perfect. Additionally, the model's performance is heavily dependent on the quality and quantity of training data, as seen in the validation accuracy (93.10% for Attention-SolarNet vs. 82.75% for SolarNet), suggesting that in regions with limited or low-quality imagery, generalization might be affected.

To address these limitations, future actions should focus on optimizing the attention mechanism to balance computational efficiency and performance gains. Expanding and diversifying the training dataset will improve generalization capabilities and robustness across different operational scenarios. Investigating hybrid architectures that combine attention mechanisms with other advanced techniques, such as transfer learning and domain adaptation, can further enhance model performance. Efficient deployment strategies for real-time applications and interdisciplinary research collaborations will also be vital to advancing the application of deep learning in solar energy systems, contributing to more efficient and sustainable renewable energy solutions.

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