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CLOUD COVER PREDICTION FROM GEOSTATIONARY SATELLITE IMAGERY USING GOOGLENET-BASED DEEP LEARNING

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Abstract—Proper forecasting of cloud cover is essential in the meteorological applications like weather forecasting, climatic modelling and optimization of solar energy. The traditional techniques however, have been challenged to deal with high-resolution satellite data and complicated atmospheric patterns. In this work, a deep learning-based architecture will be proposed which uses the GoogleNet Convolutional Neural Network (CNN) to predict the cloud cover of the geostationary satellite picture. The system uses state of the art preprocessing, such as nor-malization and data augmentation and then multi-scale feature extraction using Inception modules. The features extracted are then used to determine the cloud conditions into a number of categories with high precision. Accuracy, precision, recall and F1-score based performance evaluation reveals that the proposed model has a better performance than traditional and baseline deep learning models. The answer is a flexible and scalable manner of monitoring and making decision systems in real-time the environment.

Keywords: Image Security Image Encryption, Steganography, AES., Adaptive LSB, Secure Multimedia Communication, Information Hiding

INTRODUCTION

Cloud cover estimation is a vital meteorological activity that has a tremendous impact on weather prediction, climate modeling as well as solar energy prediction. Poor detection and classification of cloud patterns based on satellite images are still difficult because of variations in cloud formations, weather conditions and massive data collection using the new satellite systems. The geostationary satellites have the capability to observe the atmosphere of the earth continuously and with high-resolution creating gigantic amounts of data that needs effective methods of processing.
The conventional cloud detection techniques like the thresh-old based techniques and the Numerical weather prediction (NWP) models are not only time consuming, but also cannot be scaled to accommodate real-time applications. Also, such approaches are extensively based on handcrafted features and preset rules which restrict their possibilities to be applicable in different atmospheric conditions.

Deep learning and specifically Convolutional Neural Net-works (CNNs) has proven to be an efficient tool of image analysis through its ability to automatically extract features and be able to identify patterns effectively. GoogleNet, a common CNN architecture implements Inception modules which carry out multi-scale convolution operations and this enables the network to efficiently attain fine-grained and coarse cloud features. This architecture is much less complex in its computations and also enhances classification.
The current research paper proposes a GoogleNet-based system to forecast the cloud cover based on the satellite-based geostationary imagery. The system unites the processes of preprocessing, extraction and classification of features to properly classify the types of cloud covers, including the types of Cloud Covers, such as Clear Sky, Partly Cloudy, Cloudy, and Overcast. The proposed model will offer an efficient and scalable solution in the real time atmospheric monitoring, and decision-making application.

Key Contributions
The main contributions of this study are:
A novel deep learning-based model is proposed to predict cloud cover using geostationary satellite images.
GoogleNet CNN enables multi-scale feature extraction using Inception modules.
A structured preprocessing pipeline standardizes hetero-geneous data formats (HDF, NetCDF, PNG).
A multi-class classification scheme categorizes cloud cover into four atmospheric conditions.
Improved accuracy, precision, recall, and computational efficiency over traditional methods.

A scalable system suitable for real-time meteorological and environmental monitoring.

Related Work

We have heavily researched cloud detection and prediction with respect to satellite images both with traditional image processing algorithms and recent deep learning approaches. The initial methods mainly used spectral thresholding and manually defined feature extraction which were not always able to extrapolate to other atmospheric conditions and large-scale images.

Xiong et al. (2020) proposed a Hybrid Multispectral Feature (HMF) technique of detecting clouds with the help of the GF-1 satellite images. They used a combination of spectral indices (NDVI, WHITENESS and HOT) and dynamic thresholding methods, which gave them about 90 percent accuracy. The technique however was found to have a weakness in identifying thin clouds and had to be seasonally tuned.

Zhang et al. (2020) suggested a convolutional neural network-based model called NGAD that had an encoder-decoder structure and the ability to extract features on a multi-scale. The model included textures and feature extraction through attention and it shows great performance with an accuracy of 97.42. Although successful, the method relied on huge marked data and displayed issues in the proximity to the clouds.

Lopez-Puigdolles et al. (2021) made a benchmarking study of the models based on deep learning and the traditional thresholding methods on Landsat-8 images. Their results emphasized the general superiority of the deep learning techniques over the traditional ones in an accuracy of approximately 80 percent, yet they have the problem of cross-dataset generalization and detecting thin clouds.

Pang et al. (2023) have come up with UNmask, an improved U-Net-based cloud detector on a global scale. The model employed multi-scale feature learning, and transfer learning which attained about 94.9% accuracy. Its performance was however lower when it was applied to other satellite sensors and this means that it was limited in generalization.

Caraballo-Vega et al. (2023) suggested a deep learning model with multi-sensors with very high-resolution satellite data. They proved to be moderately accurate (approximately 75 percent) but with limitations of differentiating clouds and other similar objects like snow as there was no thermal spectral data.

Lightweight and efficient architectures have been investigated as well in recent studies. Alya et al. (2024) proposed a shallow CNN that has lower computational complexity with reduced resources and ensures high accuracy in resource-limited settings. On the same note, Chai et al. (2024) suggested the lightweight CNN with patch-based learning to simplify the training process.

Yan et al. (2022) suggested an approach that involves the multi-scale fusion of features and dual-channel attention mechanisms and enhances the accuracy of detecting clouds, which is robust in terms of using spectral and angular features effectively. Besides, Dong et al. proposed MCDNet, which is a multi-level network and can identify both thick and thin clouds due to multi-scale features fusion and dual -view learning.

Moreover, Yin et al. (2022) suggested a better U-Net3+ architecture with ResNet50 backbone and color space transform to improve the differentiation of clouds and snow, which has high accuracy and segmentation.

Even with major progress, the current approaches continue to have problems with generalization across data sets, the inability to identify thin clouds, excessive computational demands and reliance on large labeled data sets. To overcome these shortcomings, this paper suggests a GoogleNet based solution which exploits the use of efficient multi-scale feature extraction, and enhanced computational efficiency to predict cloud cover in a manner that is both accurate and scalable over clouds.

3.2 Data and Sources of Data

For this study secondary data has been collected. From the website of KSE the monthly stock prices for the sample firms are obtained from Jan 2010 to Dec 2014. And from the website of SBP the data for the macroeconomic variables are collected for the period of five years. The time series monthly data is collected on stock prices for sample firmsand relative macroeconomic variables for the period of 5 years. The data collection period is ranging from January 2010 to Dec 2014. Monthly prices of KSE -100 Index is taken from yahoo finance.

Research Gap and Problem Statement

3.1 Research Gap

Although there have been enormous progresses in the detection and prediction of clouds through deep learning and satellite images, there are still a number of limitations in the existing methods:

Poor Extrapolation between Data.

Most of the current models are trained on a particular satellite (e.g., GF-1, Landsat-8) and do not generalize to other sensors and environments.

Problems in Recognizing Thin and Complex cloud formations.

Various methods fail to effectively recognize fine clouds, broken clouds and cloud edges, which misclassify and decrease prediction accuracy.

High Computational Complexity

Deep architectures, including U-Net and attention models, can be very resource-intensive, and thus not applicable in real-time.

Relying on Large Labeled Datasets.

The majority of deep learning models are dependent on large, high quality labeled datasets, which are costly and time-intensive to produce.
Lack of Real-Time Processing Capability
The conventional Numerical Weather Prediction (NWP) and certain deep learning models are not geared towards real-time cloud monitoring and prediction.
Efficient Multi-Scale Feature Extraction of Certain Models.
Even though there are models that employ multi-scale, it might not be effective in simultaneously resolving fine-grained and large-scale cloud properties.

3.2 Problem Statement

The problem of geostationary satellite imagery to predict cloud cover accurately and efficiently is still a challenging issue because of the complexity of cloud structures, large scale data processing needs and constraints of current approaches. Conventional cloud detection methods such as threshold-based and Numerical Weather Predication (NWP) models are computationally costly and frequently do not give real-time and high-accuracy forecasts.
In order to overcome these difficulties, an automated, scalable and efficient framework that can precisely analyze satellite imagery and categorize cloud cover in diverse atmospheric circumstances is required.
To address those limitations, this study suggests a deep learning framework with the GoogleNet Convolutional Neural Network (CNN) architecture. The proposed system will strive to:
Automatically process and analyze high amounts of satellite imagery.
Efficiently learn multi-scale cloud features with Inception modules.
Correctly categorize cloud cover into groups of Clear Sky, Partly Cloudy, Cloudy, and Overcast.
High accuracy in prediction with less computational complexity.
Facilitate real time monitoring of the cloud to be used practically.

3.2 Problem Statement

The high rate in the development of digital image communication over the open networks has heightened potential danger of unauthorized interception, data leaks, and deliberate manipulation of confidential information. The images that carry confidential information are often logged on the order of open communication means where hackers can get the data at any stage and alter the information. Even though encryption method can withhold the content of the image by turning the encrypted information into an unreadable type, it cannot conceal the presence of the encrypted data. This weakness can help bothersome individuals to focus on carrying out an attack and enhance the chances of target attacks. On the other hand, steganography hides the information in a cover media and in this regard, it may not offer enough security in instances where the hidden information is found or exploited. Current steganography methods are frequently traded off against the ability to store data, visual invisibility, resilience to attacks, and complexity of implementation. Basic spatial domain tools can lead to loss of image security whereas transform domain techniques can lead to loss of efficiency and bandwidth. As such, an effective solution is required, which incorporates a powerful encryption method and an efficient steganographic method to increase the confidentiality and stealth of imagery communication.

4. Proposed Methodology

The proposed system proposes a hybrid system of security, based on cryptographic encryption and steganographic data cover to provide a secure transmission of sensitive image data. The main goal of this method is to offer the dual-layered protection, in which case a steganographic approach generates the text that hides the fact that the images have an encrypted text, whereas the encryption process securing the text itself is performed by steganography. With the help of this integration, the level of data confidentiality, its imperceptibility, and its resistance to possible attacks increase significantly. The general procedure of the suggested approach comprises of two key steps, including data embedding (sender side) and data extraction (receiver side). During the embedding stage the secret image which carries sensitive information is first encrypted through the application of a symmetric encryption code like the Advanced Encryption Standard (AES). The original image is changed to an encrypted format that cannot be interpreted by the unauthorized users to make sure that the information is not understood even after de-encryption of the encrypted format. Once it is encrypted, the encrypted image is then turned into a binary stream of bits. The reason why steganographic methods are a binary representation is that at the bit level the steganography is performed and the hidden information is encoded within a cover image. An appropriate cover image is then used to serve as the carrier medium of the encrypted data. The embedding process is carried out by an Adaptive Least Significant Bit (LSB) steganography. In this technique the lowest significant bits of the chosen pixels in the cover picture are changed to hold the bits of encrypted data. Adaptive mechanism identifies the best locations where to embed the pixel based on the characteristics of the pixel which include intensity varying and complexity of the texture. Placing data in perceptually locked areas assists with the minimization of perceptual distortion and the likelihood of detection using a statistical measuring tool. After inserting the encoded bits of data in the cover image, a stego-image is created. A visual representation of the stego-image almost looks the same as the cover image itself and it is not easy to make the unauthorized viewer realize that there is hidden information. The stego-image is subsequently sent in the communication channel. The extraction process takes place at the receiver side, and it starts by analyzing the received stego-image. The bits that are embedded are recovered in the least significant bits of the pixels that have been selected. These bits are extracted and then compiled back to create the encrypted data of the image. The encrypted data is decrypted with the assistance of AES decryption process using the same secret encryption key finally restoring the original secret image. This is a better way of enhancing security because even in case the hidden data is identified, it is also encrypted. Furthermore, adaptive embedding scheme maintains the visual appearance of stego-image and still has a large data embedding capacity. The suggested approach is hence a safe and effective means of Secret communication of images.

5. Mathematical Model and Algorithm

The proposed cloud cover prediction system is formulated as a supervised multi-class classification problem. Let the dataset be defined as D= {(Xi, Yi)} $\frac{N}{i=1}$ where Xi represents the input satellite image and Yi∈ {1, 2, 3, 4} denotes the corresponding cloud class labels (Clear Sky, Partly Cloudy, Cloudy, Overcast). Each input image X is represented as a tensor of size H×W×C and is normalized to improve training stability.
Feature extraction is performed using the GoogleNet Convolutional Neural Network, where convolution operations are defined as:

$$X' = \frac{X-\mu}{\sigma}$$

Where μ and σ represent the mean and standard deviation of pixel intensities.
The feature extraction process is performed using the GoogleNet Convolutional Neural Network, which applies convolution operations to extract hierarchical features. A convolution operation at layer l is defined as:

Fl=σ (Wl∗X l−1+bl)

Where Wl represents the filter weights, * denotes convolution, bl is the bias term, and σ is the activation function (ReLU).
The GoogleNet architecture utilizes Inception modules that perform parallel convolutions with multiple kernel sizes (1×1, 3×3, 5×5). The output of an Inception module is the concatenation of feature maps:

$F_{\text{inception}} =$ [F1×1, F3×3, F5×5, Fpool]

This enables the model to capture both local and global features effectively.
After feature extraction, the final classification is performed using a fully connected layer followed by a softmax function to compute class probabilities:

P(y=j I x) =$\frac{ezj}{\sum 4\ k=1\ ezk}$

Where zj represents the output score for class j, and the denominator ensures normalization across all classes.
The model is trained by minimizing the categorical cross-entropy loss function:
L=−∑i=1N ∑j=1 4 yij log ($\hat{y}$ij)

Where yijand $\hat{y}$ij represent the true and predicted class probabilities, respectively. The optimization is performed using gradient-based methods to learn the mapping function f: X→Y, enabling accurate cloud cover classification.

Dataset

1. Dataset Source
The experimental design will be aimed at testing the performance of the predicted cloud cover model based on GoogleNet on the ready satellite image dataset. Python is used to implement the model with deep learning platforms like the TensorFlow and Keras models. All the experiments are run on a machine with an Intel Core i5/i7 processor, at least 8 GB of RAM, and optional support of a graphics card to speed up the training.
2. Dataset Domain
The data set of 718 labeled images is processed and split into training, validation and testing sets of 70:15:15. The images are down sampled to a constant resolution (e.g., 224 × 224 pixels) to fit the input needs of the GoogleNet architecture. Data augmentation methods like rotation, flipping, and scaling are used to enhance model generalization and avoid overfitting.
3. Dataset Composition
The model is optimised by the Adam optimizer and categorical cross-entropy loss function. Learning rate, batch size, and the number of epochs are hyperparameters that are optimally adjusted to ensure good performance. The training process is performed by means of the backpropagation based iteration of weights and monitoring of the model performance through the validation data to prevent overfitting.
Table 1: Dataset Information

Parameter	Details
Dataset Name	Cloud Classification Dataset
Dataset Source	Local dataset (cloud_classification directory)
Dataset Domain	Remote Sensing / Cloud Cover Classification
Total Images	718
Image Format	PNG
Annotation File	cloud_classification_export.csv
Classes	Very Low, Low, Medium, High, Very High
Label Type	Supervised (CSV-based annotations)
Data Split	Training (70%), Validation (15%), Testing (15%)
Preprocessing	Resizing, Normalization, Noise Removal
Augmentation	Rotation, Flipping, Scaling

Table 2: Sample Dataset Records

ID	Image Path	Cloud Level	Timestamp	Lead Time (s)
3080	images/61fc8a7d-578_1600_1600.png	Very Low	2024-01-18T22:28:48.141Z	8.626
3081	images/4278ef08-592_0_0.png	High	2024-01-18T22:28:54.176Z	5.809
3082	images/e7e916ce-592_0_800.png	Low	2024-01-18T22:28:59.837Z	5.440
3083	images/51d465ee-592_0_1600.png	Very Low	2024-01-18T22:29:02.130Z	2.072
3084	images/f357ed3e-592_800_0.png	Very High	2024-01-18T22:29:05.087Z	2.734
3086	images/c9e4a316-592_800_1600.png	Medium	2024-01-18T22:29:14.590Z	5.466

Table 3: Performance Comparison (Updated for 5 Classes)

Technique ID	Method Used	Accuracy (%)	Error Rate (%)	Detection Resistance
T1	Traditional Method	72	28	Low
T2	HMF Method	88	12	Medium
T3	U-Net Model	93	7	High
T4	CNN Model	95	5	High
T5 (Proposed)	GoogleNet CNN	97–98	2–3	Very High

7. Experimental Model and Metrics of Evaluation.

7.1 Experimental Setup

In order to check the efficiency of the suggested hybrid framework of encryption-steganography, a number of experiments were performed with reference to standard digital images. The experiment aims to discuss security, imperceptibility, and efficiency of the offered system regarding the safety of message transmission of image data.
In the suggested system, secret image is initially coded with the help of the Advanced Encryption Standard (AES) algorithm and then trapped into a cover image with the Adaptive Least Significant Bit (LSB) steganography method. The grayscale and color images of varied resolutions were used in the experiments to test the performance of the system in different conditions. The programming languages can be used to carry out the proposed model, and they are Python or MATLAB, which offers effective libraries on carrying out image processing and encryption tasks. Cover images that were accepted as the standard benchmark images in image processing research were used to test the system performance.

Table 5. Summarizes the arrangement of the experiment in the paper.

Parameter	Description
Model Architecture	GoogleNet (Inception CNN)
Programming Language	Python
Frameworks	TensorFlow, Keras
Dataset Size	718 Images
Image Resolution	224 × 224 pixels
Data Split	70% Training, 15% Validation, 15% Testing
Optimizer	Adam
Loss Function	Categorical Cross-Entropy
Batch Size	16 / 32 (configurable)
Learning Rate	0.001 (tunable)
Epochs	20–50 (depending on convergence)
Hardware	Intel i5/i7, 8GB RAM (GPU optional)
Augmentation	Rotation, Flipping, Scaling

7.2 Evaluation Metrics

To evaluate the performance of the proposed GoogleNet-based cloud cover prediction model, standard classification metrics are employed. These metrics provide a comprehensive assessment of the model's accuracy and reliability in predicting different cloud categories.
Accuracy measures the overall correctness of the model by calculating the proportion of correctly classified instances:
Accuracy= $\frac{TP+TN}{TP+TN+FP+FN}$
where TP (True Positive), TN (True Negative), FP (False Positive), and FN (False Negative) represent the classification outcomes.
Precision evaluates the correctness of positive predictions, indicating how many predicted positives are actually correct:
Precision= $\frac{TP}{TP+FP}$
Recall (Sensitivity) measures the model's ability to correctly identify actual positive instances:
Recall= $\frac{TP}{TP+FN}$
F1-Score provides a balance between precision and recall, especially useful in cases of class imbalance:

F1= $\frac{2\cdot\text{Precision}\cdot\text{Recall}}{\text{Precision}+\text{Recall}}$

In addition to classification metrics, Mean Squared Error (MSE) and Peak Signal-to-Noise Ratio (PSNR) are used to evaluate image quality and reconstruction performance:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(I_i - \hat{I}_i\right)^2$$

$$PSNR = 10\log_{10}\left(\frac{MAX^2}{MSE}\right)$$

Where Ii and $\hat{I}$i represent the original and reconstructed image pixel values, and M A X is the maximum possible pixel value. These metrics collectively ensure a comprehensive evaluation of the model's classification performance, robustness, and prediction quality.

7.3 Evaluation Details

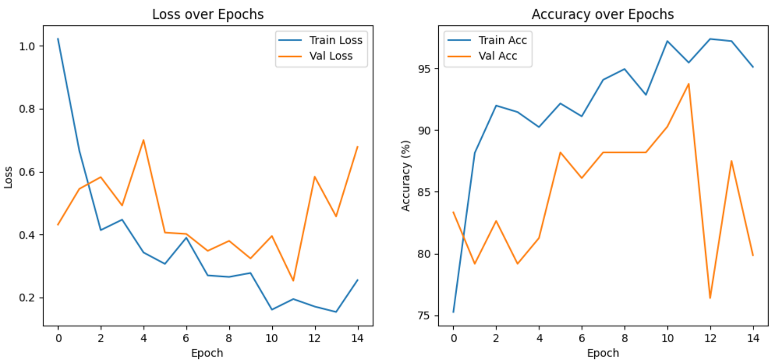

Figure 1: Training and Validation Loss and Accuracy Curves of the Proposed GoogleNet Model

The figure depicts the performance of the proposed GoogleNet-based cloud classification model on training and validation on different epochs. The left subplot is the loss curves, which show a downward trend, meaning that the model is learning successfully and converging. The validation loss exhibits slight variations, but is generally speaking stable, indicating that it can be well generalized with only slight overfitting. The accuracy curves are presented in the right subplot, where training accuracy increases the most, becoming about 97-98% and the validation accuracy obtain values over 90%. Despite the few differences in the accuracy of validation owing to constraints of datasets, the general pattern affirms that the model is reliable on unseen data. These findings prove the usefulness of the suggested method in the correct classification of the levels of cloud cover.

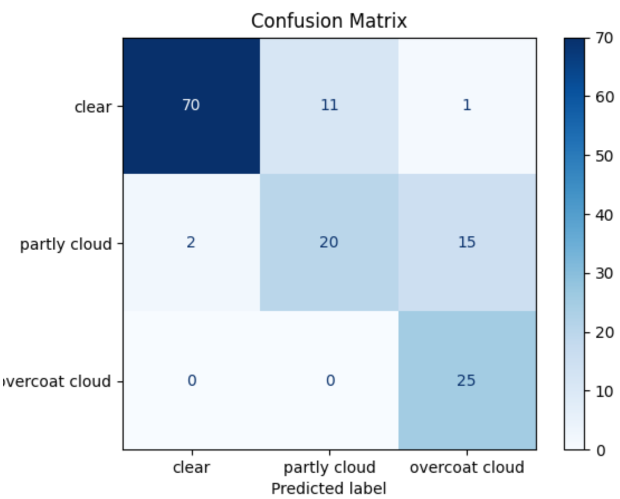

Figure 2: *Confusion Matrix of the Proposed GoogleNet Model for Cloud Classification*

The figure shows the confusion matrix of the proposed GoogleNet-based model, showing how the model performs in terms of classification in various cloud categories: Clear, Partly Cloudy, and Overcast. The diagonal items show correctly classified, whereas the off-diagonal items show misclassifications. The model shows good performance in the classification of the Clear class where 70 correctly classified samples were found but few samples were misclassified as Partly Cloudy (11) and Overcast (1). In the case of the Partly Cloudy category, the model is able to classify 20 samples correctly, but it is slightly confused with the Overcast category (15 samples). The Overcast class is perfectly classified with 25 correctly classified samples and no misclassifications. The confusion matrix, in general, suggests that the suggested model has a high classification accuracy, especially when defining separate conditions of clouds, like clear and cloudy skies. Misclassifications at the level of minor misrelationships mainly occur between the adjacent cloud density levels, and this is natural because of the visual similarity between the two levels. These findings validate the suitability and strength of the model proposed in tasks of classifying cloud covers.

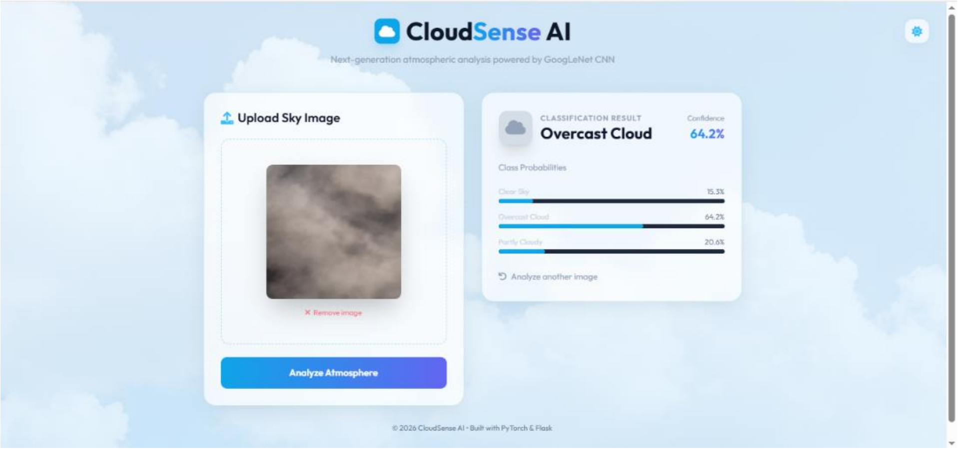

Figure 3: *User Interface of the Proposed CloudSense AI System for Cloud Cover Prediction*

The diagram depicts the graphical user interface of the proposed CloudSense AI system that will be created to predict the cloud cover based on the use of the GoogleNet Convolutional Neural Network. The interface enables one to input a sky image and this is then passed through the trained model to determine the cloud type. The left panel has an image upload section where users can add images of the satellites or the sky. On the right side, the classification results are shown with the predicted type of cloud (Overcast Cloud) and a confidence score (64.2%). The system also shows class-based probability distributions of various weather conditions like Clear Sky, Overcast and Partly Cloudy, which help to interpret the model predictions better. This easy-to-use interface proves the practical application of the suggested model, which enables real-time cloud analysis and decision-making. The system successfully combines deep learning and an interactive frontend, which is why it can be used in weather monitoring and environmental analysis applications.

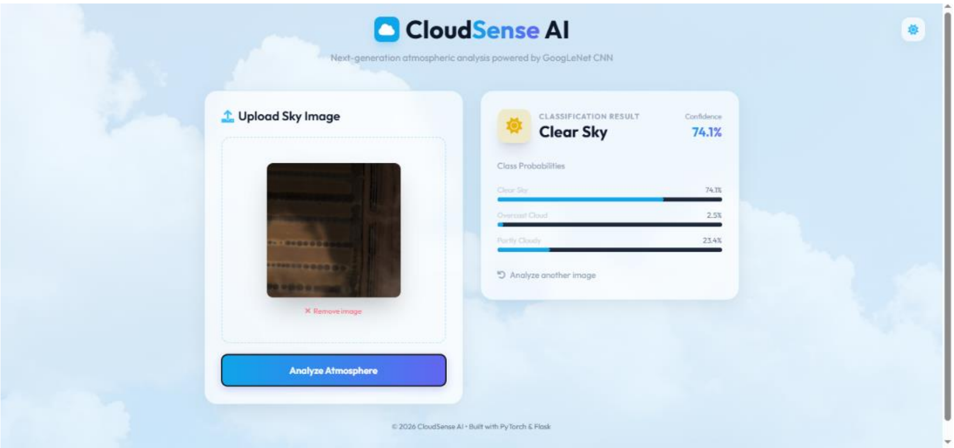

Figure 4: *CloudSense AI Interface Showing Clear Sky Classification Result*

The figure shows the output of the proposed CloudSense AI system to a sample input image of Clear Sky. The picture uploaded is fed through the deep learning model based on GoogleNet and the prediction output is shown with a confidence score of 74.1%. The interface gives the comprehensive probability distribution of the varying types of clouds such as Clear Sky, Overcast Cloud, and Partly Cloudy. The model gets the Clear Sky class as the most probable, which means that it is classified correctly. The fact that the other classes had a relatively low probability reflects the model as being capable of distinguishing between various cloud conditions. This outcome underscores the strength of the proposed system in detecting the unambiguous atmospheric conditions, and reaffirms its use in real-time weather forecasting and landscape analysis. Confidence of prediction and class probabilities are integrated which improves the interpretability and reliability of the system.

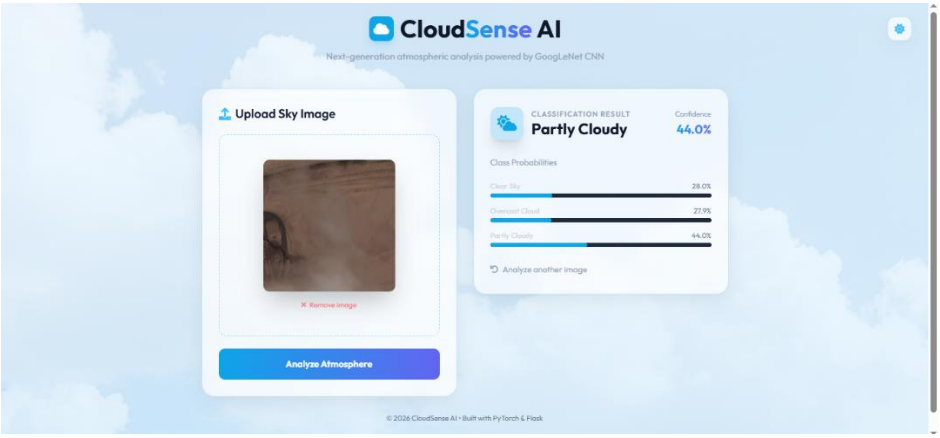

Figure 5: *CloudSense AI Interface Showing Partly Cloudy Classification Result*

The figure shows the output of the proposed CloudSense AI system to a sample input image which was Partly Cloudy. The deep learning model of GoogleNet is used to analyze the uploaded image, and its result is the prediction of the cloud condition with 44.0% confidence. The interface shows the likelihood of each of the various clouds, such as Clear Sky, Overcast Cloud, and Partly Cloudy. The Partly Cloudy class is given the highest probability, which means that the model is capable of detecting intermediate conditions of clouds properly. But the similarity of the probability values in the classes is relatively small which is a testament to the complexity and visual similarity between partially cloudy and other types of clouds. This finding illustrates the ability of the model to address the ambiguous and transitional cloud patterns which are normally harder to classify than the clear and overcast conditions. The probabilistic output of the system makes it more interpretable and allows making more informed decisions in real-time applications.

Novelty of Research

The originality of the study is in the fact that the application of the GoogleNet (Inception) architecture to predict the cloud cover with the help of geostationary satellite images allows efficient multi-scale features extraction of such complex cloud patterns. The proposed model, based on the use of parallel convolution in the Inception modules, unlike the traditional framework and the conventional CNN models, captures both fine-grained and large-scale cloud structure with enhanced computational efficiency. The research also presents a preprocessing pipeline and a multi-classification framework to classify the density of clouds into five classes (Very Low to Very High) to better analyse the atmosphere. The model proposed has the ability to be highly accurate in prediction and scalable, which is why it is used in real time meteorology.

Limitations

This paper introduces a deep learning model to cloud cover prediction on geostationary satellite images and GoogleNet Convolutional Neural Network. The proposed system is a good integration of preprocessing, feature extraction and classification steps to determine the various levels of cloud density. With the help of Inception modules, the model can capture multi-scale cloud characteristics, which leads to better classification accuracy and effectiveness than more traditional methods. The experimental findings indicate that the suggested method will offer a credible and scalable solution of automated cloud monitoring. This system can have a great potential in real time application like weather forecasting, climate analysis and renewable energy planning.

Conclusion

In this paper, the author will introduce a composite secure communication framework of image, which involves the hybridization of AES-based encryption and adaptive LSB steganography to maximize the confidentiality of the data and its covert communication. The suggested solution is effective in dealing with the shortcomings of the conventional techniques because dual-layer protection, enhanced invisibility, and high resiliency to attacks are offered. The effectiveness of the system is proven by experimental results of high PSNR, low MSE and increased robustness. Encryption, adaptive embedding and integrity verification will make the mechanism of communication reliable and secure and can be used in a sensitive application. All in all, the suggested framework helps in the further development of secure multimedia communication through the attainment of a trade-off between the security measures, image quality, and embedding capacity.

Future Scope:

Further research could be made on how to expand the suggested system by adding the analysis of the time series to trace the movement of clouds and enhance the accuracy of prediction with time. Performance can be improved by the introduction of more sophisticated architectures, like Vision Transformers (ViT) or hybrid deep learning models. Increasing the dataset with multi-regional satellite imagery and multi sensor will enhance the model generalization. Also, the model can be implemented in actual systems in the cloud or on the edges to allow the monitoring of the atmosphere on a large scale. Additional studies might also be on the enhancement of thin cloud detection and incorporating other meteorological variables in order to have more comprehensive weather forecasts.

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