

Automatic Segmentation of Cloud Image from Satellite Image

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ABSTRACT: The precise and reliable interpretation of the objects on land is hampered by the presence of clouds in satellite photography. Therefore, before allowing the satellite images to be used for any additional analysis, automatic cloud detection is an essential pre-processing step. The different densities and thicknesses of clouds make this a difficult operation. A Deep Learning (DL)-based system for automatically segmenting clouds from satellite data is proposed in this research to improve the accuracy of climate models. The system uses a Long Short-Term Memory (LSTM) network that is connected with a systematic workflow that includes feature extraction of Histogram of Oriented Gradients (HOG), model training, and data preprocessing of Contrast Limited Adaptive Histogram Equalization (CLAHE). Raw satellite datasets are first preprocessed and pertinent features are extracted. An LSTM-based model uses these features and trained to identify temporal patterns in order to improve cloud formation prediction. Future cloud topologies are predicted by the trained model using historical data, and users can access these predictions. The model is trained and verified using publicly accessible satellite image datasets and is implemented using PyTorch and its related libraries. A comparison with conventional rule-based segmentation techniques demonstrates that the proposed method captures a variety of cloud structures.

Keywords: Satellite Image, Data Preprocessing, Feature Extraction, Long Short-Term Memory, Segmentation.

1. Introduction

With the growing availability of high-resolution satellite imagery, accurate and efficient detection of cloud cover has become increasingly important in various remote sensing applications such as weather forecasting, climate monitoring, solar energy estimation, and land-use analysis [1-2]. Clouds are composed of water droplets and ice crystals that scatter and absorb sunlight, especially in the visible and infrared wavelengths, leading to reduced image clarity and contrast. Thick or multi-layered cloud formations can completely obscure ground features, while thin or semi-transparent clouds, such as cirrus clouds, may blur the image by diffusing light unevenly [3]. Additionally,

clouds introduce brightness variability and cast shadows on the Earth's surface, which further distorts image interpretation. One of the primary distractions comes from bright surface features such as snow, ice, deserts, and urban areas, which can appear visually similar to clouds due to their high reflectance, leading to false positives during segmentation [4-5]. These factors make it difficult to extract reliable information from cloudy images, necessitating cloud detection and masking techniques as part of satellite image analysis workflows. Therefore, many segmentation and classification techniques from ML and DL are utilized to rapidly recognize [6]. Numerous Machine Learning (ML) techniques have been

employed, most of which concentrate on the distinction the classification of the satellite imaging. ML techniques such as Random Forest, Decision Tree, and Support Vector Machine (SVM) help with the detection and classification [7-8]. This technique causes a time delay, and poor-quality data leads to inaccurate predictions and misguided insights. There are certain drawbacks to ML. Therefore, DL is mostly employed for difficult tasks, so this work uses a DL algorithm [9]. While CNNs are highly effective in extracting spatial features from satellite images, they lack the ability to capture temporal dependencies a critical aspect in satellite imagery where cloud formations evolve over time. LSTMs overcome this limitation by retaining and learning long-term sequential patterns, making them ideal for applications where time-series or sequential satellite data is available [10]. Therefore, this paper presents a deep learning-based segmentation system for automatically segmenting clouds from satellite data with the highest accuracy. In this work, the following contributions are achieved:

- To enhance the quality and remove the noise of the image, employ a CLAHE filter.
- To extract the features for image detection quickly and accurately by using the HOG technique.
- To segment the accurate cloud satellite images, LSTM segmentation is used.
- To evaluate the accuracy by using a DL - based LSTM model.

The order in which the paper is given is shown in the list below: Section II covers the most recent work. Section III provides a detailed description of the proposed work. The results are shown in Section IV. Section V provides a conclusion.

2. Recent Works

Marc Wieland *et al* (2024) [11] have presented a CNN model for semantic segmentation of surface water bodies in publicly available Sentinel-1 and

Sentinel-2 satellite images. It performs well even with small datasets and is highly effective in capturing detailed cloud structures. Its performance is significantly improving as a consequence, reaching an impressive accuracy. Furthermore, it may not preserve fine-grained localization unless combined with upsampling.

Irem Ulku *et al* (2022) [12] have developed a deep Semantic Segmentation for the multispectral imagery. It reduces computational costs and achieves the highest performance and classification accuracy in the short amount of time. It's simple and consistent design, making it easy to implement and modify. However, it is not ideal for tasks that require real-time processing or low hardware resources.

Jiajun Yang *et al* (2024) [13] have proposed a Generative Adversarial Networks (GANs) for weakly supervised cloud and snow detection method. It obtains the generated remote sensing images and corresponding pseudo labels. Further, it achieves superior cloud and snow detection performance. The vanishing gradient problems make training a deeper network more complex, and at a certain depth, accuracy continues to drastically decline.

Taoyang Wang *et al* (2022) [14] have presented an UNet++ technique for the optical satellite video smoke target segmentation. It yields the greatest results in terms of validation accuracy and more accurately and efficiently detects. However, collecting a significant volume of annotated data is sometimes unfeasible and unavailable in fields. It requires careful tuning and is computationally intensive for long sequences.

Kamil Choromanski *et al* (2022) [15] have developed a VGG-16-based network for meridiani planum's aeolian landscape images analysis. It has strong transfer learning performance, highly structured and consistent and effective in remote sensing and cloud segmentation. However, it lacks the ability to capture temporal dynamics, making

them less effective for tracking cloud movement over time.

3. Proposed Work Explanation

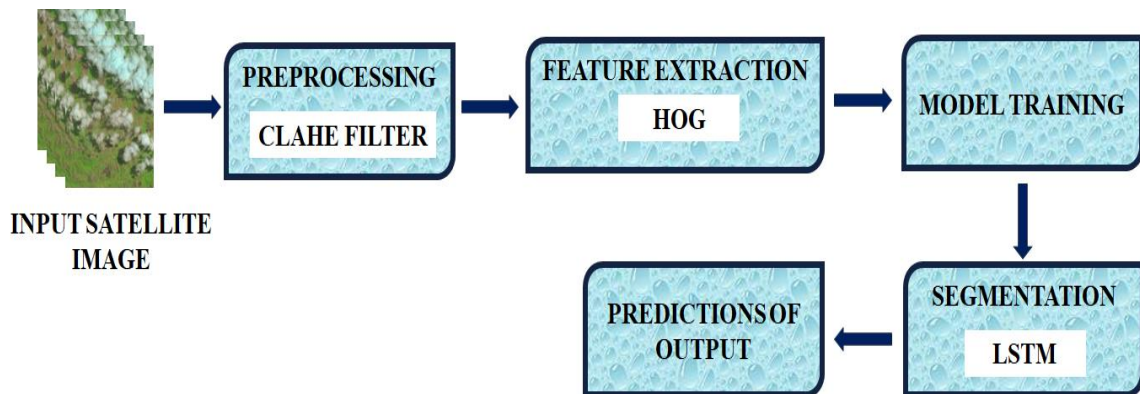


Figure 1: Block Diagram for Proposed System

The initial stage of preprocessing allows an analysis of the input image by using the CLAHE filter, which works to remove noise and enhance the visibility of blurred images. HOG handles the extraction step for this modulus after preprocessing. It extracts the features for image segmentation quickly and accurately. For the extracted features, the following segmentation process. This image segmentation technique classifies pixels based on their intensity values. Further, it provides the final prediction, with excellent specificity and sensitivity for classifying images as offering the final step.

3.1 Pre-processing

Satellite images often suffer from various imperfections such as noise, low contrast, atmospheric distortion, and irrelevant background information that hinder precise cloud detection. So, pre-processing is a critical step in any data-driven system, including machine learning, signal processing, image analysis, and control applications. The main goal of pre-processing is to enhance the quality, consistency, and relevance of the data by removing noise, normalizing values, handling missing entries, and transforming inputs into a format suitable for further analysis or computation.

3.1.1 CLAHE Filter

This proposed work uses a LSTM network method to segment the cloud image from satellite image. Figure 1 displays the proposed system's block diagram.

In this work, CLAHE filter is used to enhance image quality, reduce artifacts, and highlight meaningful features. This filter is an advanced image enhancement technique widely used in image processing applications, including satellite image analysis, medical imaging, and computer vision tasks like segmentation. It works by improving the local contrast of an image by dividing it into small regions or tiles and applying histogram equalization to each one individually, rather than using the global histogram. Further, it improves image quality, lowers noise, and increases the efficiency of later processes like feature extraction or segmentation in the context of satellite imaging.

3.2 Feature Extraction

After pre-processing enhances the quality and clarity of the image, feature extraction identifies key characteristics such as texture, intensity, shape, edges, spatial patterns, and spectral information across different bands. It transforms preprocessed image data into a set of meaningful and quantifiable attributes that distinguish cloud regions from the background. enables more precise segmentation by ensuring that classification or clustering algorithms effectively differentiate cloud pixels from non-cloud elements like land, water, and shadows. Thus, this

work uses HOG for improving the accuracy, speed, and reliability of cloud segmentation in satellite image analysis.

3.2.1 HOG Technique

It is a powerful feature extraction technique widely used in image processing and computer vision for object detection and image classification tasks. In the context of satellite cloud image segmentation, HOG can be used to capture the shape, structure, and edge information of cloud formations. The feature vectors formed by concatenating these histograms effectively describe the spatial arrangement and patterns in cloud shapes, making them suitable for distinguishing between different cloud types or separating clouds from background elements. Further, it is a reliable pre-processing step for machine learning classifiers or segmentation models in cloud detection and other remote sensing applications.

3.3 Model Training

After pre-processing and feature extraction, labelled datasets where pixels or regions are annotated as cloud or background are used to train the model. During training, the model adjusts its internal parameters to minimize the error between its predictions and the actual labels. The model iteratively processes training samples, computes a loss function, and updates itself using optimization algorithms like gradient descent. Proper model training includes data augmentation, cross-validation, and hyperparameter tuning to improve generalization and prevent overfitting. Once trained, the model can accurately segment cloud regions from new, unseen satellite images, making it a powerful tool for automated cloud detection and climate monitoring applications.

3.4 Image Segmentation

Image segmentation is the core process in the automatic segmentation of cloud images from satellite imagery, where the image is partitioned into meaningful regions specifically separating

cloud areas from the background such as land, ocean, or atmosphere. The goal of segmentation is to assign a label to each pixel in the image, grouping similar pixels together based on features like color, intensity, texture, or spatial proximity. Further, it ensures that only relevant cloud features are extracted for further analysis, enabling better performance in weather prediction, climate modeling, and remote sensing applications. Numerous segmentations are employed in this procedure for more accuracy and less dependence on manual intervention. So, one of the LSTM segmentations is used in this work for improving the reliability and efficiency of satellite-based Earth observation systems.

3.4.1 LSTM

LSTM networks are specialized Recurrent Neural Networks (RNNs) designed to learn patterns in sequential data by maintaining memory over long-time intervals. In the context of satellite-based cloud image segmentation, LSTMs are particularly valuable when dealing with temporal sequences of images that is, multiple satellite images of the same location captured over time. LSTM networks use a memory cell and a set of gating mechanisms namely the input gate, forget gate, and output gate to regulate the flow of information through time. The LSTM architecture is shown in Figure 2.

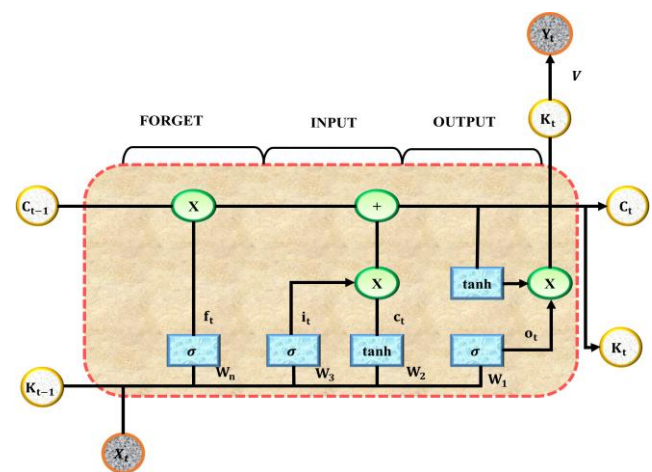


Figure 2: LSTM Architecture

The input gate controls how much of the new input should be written to the memory cell, the forget

gate determines what information should be discarded from the previous cell state, and the output gate decides how much of the memory should be exposed to the next hidden state. These gates are controlled by sigmoid activation functions, while the memory content is updated using a tanh function.

3.4.2 Input Gate (i_t)

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (1)$$

What additional data gets introduced to the cell state is decided by this gate.

3.4.3 Cell State (C_t)

$$C_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \quad (2)$$

The "memory" of the LSTM unit, which carries information across time steps.

3.4.4 Hidden State (h_t)

$$h_t = o_t \cdot \tanh(C_t) \quad (3)$$

This output, which includes the learnt data needed for prediction, comes from the LSTM unit at a certain time step.

3.4.5 Forget Gate (f_t)

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (4)$$

Which data from the prior cell state are deleted is determined by this gate.

3.4.5 Output Gate (o_t)

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (5)$$

The portion of the cell state that are produced at the current time step is determined by this gate. In cloud segmentation tasks, LSTM networks process a series of images captured over time to track the movement, development, and dissipation of clouds. It handles spatial feature extraction, while the LSTM layers model the temporal evolution of cloud features. This leads to more accurate and context-aware segmentation, especially in dynamic weather systems. Overall, LSTM enhances cloud segmentation performance by adding a temporal learning capability, enabling

better analysis of cloud behavior across time and improving forecasting accuracy in meteorological applications.

4. Results and Discussion

In this paper, the system established analyzes and segments the cloud images from satellite imagery. Additionally, the work implemented using a PyTorch software program to attain the outcomes is covered below.

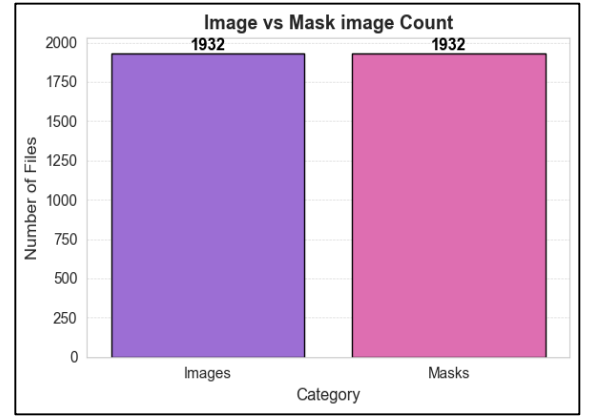


Figure 3: Count of the Input Image

Figure 3 displays the count of the input of the cloud input images. In case input images are attaining the count of 1932 datasets. Similarly, the mask images or hidden parts of the images are attained from the same count of the datasets.

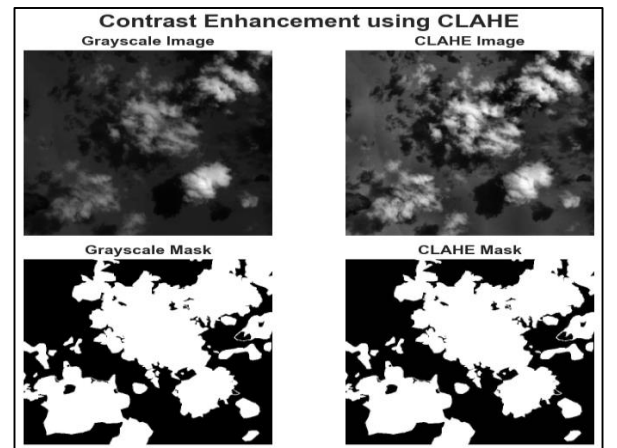


Figure 4: Filtered Images

Figure 4 illustrates the filtered images in various input images. The input images appear as the grayscale image and filtered image after being preprocessed using the CLAHE filter, and results are displayed.

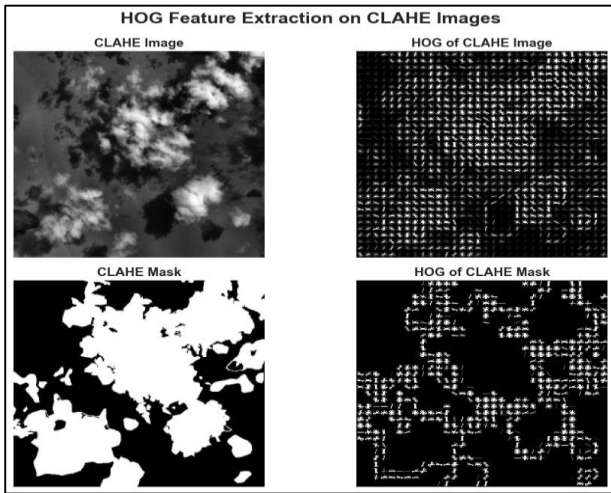


Figure 5: *Extracted Images*

Figure 5 depicts the extracted images using HOG feature extraction. The filtered images are displayed in the first column. The extracted images are then placed in the second column once the HOG technique is applied.

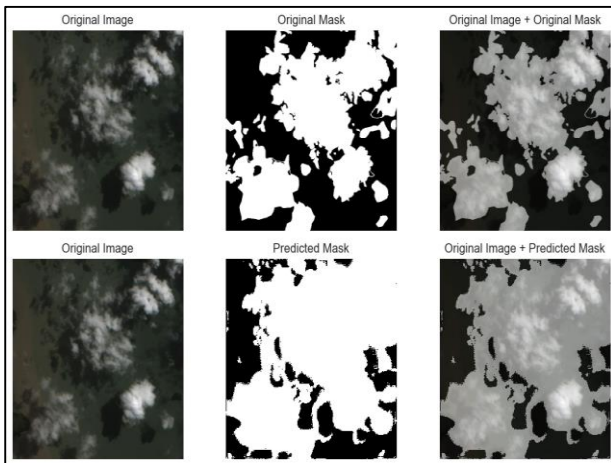


Figure 6: *Predictions of output*

The prediction of outputs is illustrated in Figure 6. The input images appear in the first column after being preprocessed using the CLAHE filter, these results are displayed in the second column. Following that, the LSTM segmentation offers an effective technique for segmenting the accurately from the images that are in the last columns.

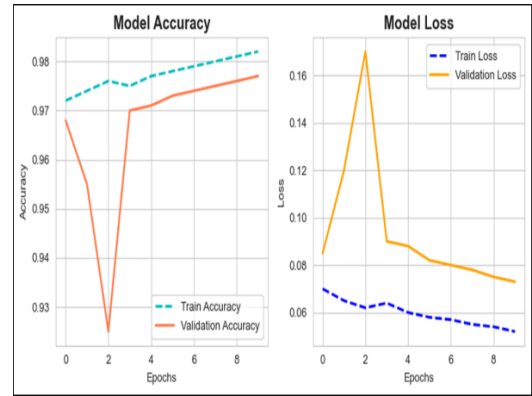


Figure 7: *Model Accuracy and Model Loss*

Figure 7 shows the accuracy and loss of the model. Accuracy curves and training and validation losses are clearly seen in the figure, respectively. This proved that the proposed strategy is segmenting the satellite images more accurately than single feature extraction methods.

Table 1: *Comparison performance of various classifications*

SEGMENTAIONS	ACCURACY %	LOSS %
UNET++ [14]	91.78	0.75
VGG 16 [15]	94.32	0.43
CNN [11]	97.34	0.25
LSTM [Proposed]	98.97	0.17

Table 1 shows the accuracy and loss values of the proposed approach in comparison to alternative approaches. According to the findings of comparing the proposed strategy with other algorithms, it outperforms the others in terms of segmentation.

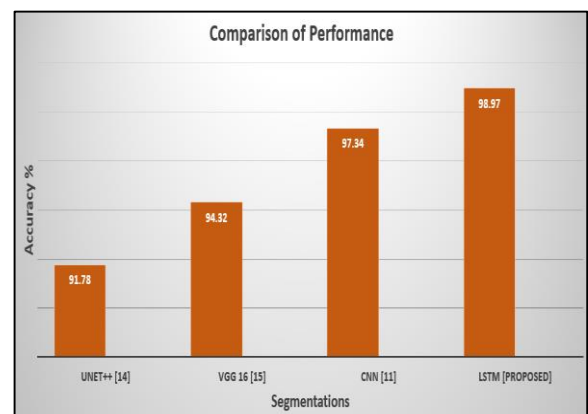


Figure 8: *Comparison of Performance*

The performance of the proposed LSTM segmentation and a comparative graph of several classes are shown in Figure 8. Several classifications with accuracy values, such as UNET++ [14], VGG 16 [15], and CNN [11], have been analysed. The proposed approach demonstrated the highest accuracy of 98.97% with the highest performance.

4. Conclusion

The automatic segmentation of cloud images from satellite imagery is a vital process in modern remote sensing, offering significant improvements. This paper provides an automatic segmentation technique of LSTM implemented for accurate, clear cloud satellite images. Pre-processing steps enhance image quality, feature extraction highlights meaningful patterns, and intelligent segmentation models ensure accurate cloud boundary detection. In results, accuracy of 98.97% and minimum loss of 0.17% are achieved for automatic segmentation of satellite images. This work supports real-time weather forecasting and climate monitoring and also aids in solar energy prediction, land-cover analysis, and disaster management. Overall, it enhances the utility of satellite data, making it a powerful tool for environmental observation and decision-making in a wide range of geospatial and meteorological applications.

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