Grenze International Journal of Engineering and Technology, June Issue

Cloud Detection and Nowcasting for Ship Navigation

Mahalakshmi Sreenivasan[1], Kanuri S V S Sai Kumar[2] and P.Selvaraj[3]
[1-3]Department of Computing Technologies, Faculty of Engineering and Technology, School of Computing, SRM Institute of Science and Technology, Kattankulathur, Chennai, 603203, Tamil Nadu, India
Email: ms4934@srmist.edu.in, kv8700@srmist.edu.in, selvarap@srmist.edu.in

***Abstract*— Navigating through oceans is challenging. Sailors are disadvantaged in determining the most appropriate and safe path, free from hurdles and extreme weather conditions, especially on pitch-dark nights. Ships rely on their communication with satellites for navigation. When this connection breaks, the ship loses its ability to navigate and follow the required path. In such scenarios, the Geographical Information System (GIS) and Satellite Imagery-based algorithms are best suited to assist. It is necessary to focus on cloud behavior to ensure the success of ocean endeavors. Cloud Detection is performed by the methods of K-Means clustering and MRCNN. The approach of Mean Path Adjustment (MPA) is used to trace the center of mass to predict Cloud Motion; thereby, building a convolutional LSTM model for Cloud Nowcasting. Collectively, these methods help in detecting clouds, predicting their motion, and helping sailors decide the route to follow, based on the weather conditions. This system works well when the communication between the ship and satellite breaks. A high similarity index of 0.8363 is achieved with the test images.**

***Index Terms*— Satellite Imagery, Navigation, Cloud Detection, Cloud Nowcasting, Machine Learning (ML), Mask RCNN (MRCNN), Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), Convolutional LSTM**

I. INTRODUCTION

Clouds are extremely dense and voluminous masses that appear to the unaided eye. They play a crucial role in the Earth's biosphere, providing rain and snow, protection from harmful radiation, and cooling the surroundings. Clouds help comprehend the weather and climate. Their influence extends to various aspects of human life such as agriculture, notably navigation. Cloud behavior is essential in determining the possibility of a calm or vigorous forecast, especially in oceanic regions where weather is unpredictable. It helps sailors in deciding the oceanic route or path to be followed, based on the cloud density, and predicted motion. Two primary approaches to Cloud Detection are explored in [1]. It includes the ML approaches and traditional algorithms. ML methods are employed to learn from the training data while traditional algorithms utilize intensity thresholds to distinguish between cloudy and clear regions and identify various cloud types. The methods of block matching and linear extraction of cloud characteristics are often employed for cloud motion prediction, and they rely on cross-correlation and spectral approaches to create an estimate. Neural Networks, Deep Learning, and the Lukas-Kanade Optical Flow Methods too have been gaining popularity. They directly predict cloud motion from ground-based cloud images. Due to their slow movement, cloud motion is predicted as a sequence of positions. However, these methods pose a major threat: loss of connection. When the satellite and ship lose communication, the ships need to receive the

Grenze ID: 01.GIJET.10.2.260

last batch of cloud images to predict the sequential motion; thereby adjusting the ship's route. The lack of flexibility too plays a spoilsport. The methods proposed by various researchers pertain only to a particular dataset or set of images, that is, they lack standardization. Due to strict rules and regulations, access to real-time satellite imagery data is difficult. So, researchers mostly stick to available datasets and ground-based cloud images. The proposed solution integrates cloud detection and nowcasting, followed by a developed web application for the INSAT-3D geosynchronous satellite data. Cloud is detected by the comparison of a clustering algorithm and RCNN approach. CNN and LSTM are utilized in tandem to perform the Nowcasting or prediction of motion. This system also works in the absence or loss of communication between the ships and INSAT.

II. State-Of-The-Art

Clouds are visible masses of water vapor. They bring rain but hinder visibility. It is necessary to preprocess and detect them for various applications in remote sensing. Cloud Detection is usually performed using the properties of clouds such as shape, color, spectral contents, bands (such as TIR and VIS), and angles. Sun et al. [2] suggested a Cloud Detection method that utilizes dynamic thresholds to address challenges in conventional cloud detection methods, such as mixed pixels and atmospheric factors. It utilizes a monthly surface reflectance database generated from Moderate Resolution Imaging Spectroradiometer (MODIS) data. Under varied situations, this approach provides connections between apparent reflectance changes and surface reflectance. Experiments on Landsat 8 and MODIS demonstrate that UDTCDA has an 81% accuracy in cloud identification. Philippe Reiter [3] used the theory of Wavelet Transforms (WT) for image and signal processing transforms. It is a powerful signal compressor and feature extractor for machine learning and deep learning classifiers and this system has been deployed to operate in real-time for low-power devices. Shao et al. [4] proposed the approach of Multiscale Features CNN for detecting clouds in remote sensing images. It concurrently detects thin clouds, thick clouds, and non-cloud pixels in Landsat 8 satellite imagery. Experimental results demonstrate superior performance compared to common cloud detection methods. Wei et al. [5] proposed a cloud identification technique for urban areas by analyzing color and edge features in remote-sensing images. Through superposition analysis, a cloud map is obtained and used to linearly stretch the image for enhanced thin cloud detection. A threshold technique is applied to create a thin cloud region map, which is then combined with the cloud map for a complete region map. Cloud masking is crucial in remote sensing to identify and eliminate cloud-covered regions from satellite imagery. It ensures accurate analysis of the Earth's surface, supporting applications like navigation, land cover monitoring, agricultural assessments, and disaster response. Luis et al. [6] addressed the technique of generating cloud masks automatically in Earth remote-sensing images for processing satellite time series data. The method estimates background surface changes using least squares regression algorithms, minimizing prediction and estimation errors simultaneously. Tested on SPOT-4 and Landsat-8 datasets, the algorithm outperforms cutting-edge techniques, providing more accurate cloud masks. Xie et al. [7] introduced the Oriented R-CNN, a two-staged oriented object detection framework designed to address the computational bottleneck in current state-of-the-art detectors. The first step utilizes an oriented RPN, which produces excellent suggestions efficiently. At the end of it all, Oriented R-CNN alongside ResNet50 achieves top-tier detection accuracy. Kaiming et al. [8] proposed Mask RCNN, a versatile framework for object instance segmentation. It extends Faster RCNN and identifies objects and produces high-quality segmentation masks alongside. Ren et al. [9] identified the Region Proposal Network (RPN) that efficiently generates region proposals at nearly no additional cost by sharing the network's convolutional features for identifying objects. It is a complete CNN that predicts object limits and objectness scores simultaneously at every pixel. When trained from start to finish, it generates high-quality region recommendations that Fast R-CNN may employ for object detection. Cloud Motion Prediction and Nowcasting is advantageous for anticipating the movement of clouds over time, enabling more accurate short-term weather forecasts. Su et al. [10] proposed complex deep learning model Multi-GRU-RCN, treating cloud motion as a sequence-forecasting problem. Utilizing GRU and RCN, the model incorporates convolutional features for spatiotemporal feature handling. The approach outperforms novel methods by demonstrating superior cloud-motion prediction as measured by the maximum ratio of signal over noise and the underlying similarity coefficient. The findings demonstrate the model's usefulness and advantages for spatiotemporal data prediction. Lu et al. [11] introduced a nowcasting method for ground-based cloud images using Cascade Causal LSTM and SR-Net. They estimate the motion shape, and speed and reconstruct the results for clarity. Tested on Atmospheric Radiation Measurement (ARM) TSI images, the method accurately predicts sky cloud changes in subsequent steps, addressing limitations of traditional image processing and motion vector calculation methods. Ye et al. [12] introduced the Temporal Point Cloud Networks (TPCN), a framework for trajectory prediction that combines spatial and periodic learning. It employs cloud point learning and variable periodic learning. Agents are represented as an unordered point set in the spatial dimension, utilizing the above. Variable periodic learning captures the movement of agents throughout time. Most of the above research revolves around cloud detection and nowcasting done separately. This proposed work shows that they are interdependent in many real-world applications.

III. Cloud Detection And Nowcasting

A Dataset

INSAT-3D is a meteorological satellite operated by the Indian Space Research Organization (ISRO). It belongs to the Indian National Satellite System (INSAT) program, which aims to provide various services including meteorology, telecommunications, broadcasting, and search and rescue operations. INSAT-3D, like many meteorological satellites, captures imagery in different spectral bands to observe various aspects of the Earth's atmosphere. Two important types of images produced by INSAT-3D are the Visible (VIS) images and the Thermal Infrared (TIR) images. The dataset focuses on images taken on 7th November 2019, creating a time series spanning 24 hours with intervals of 30 minutes.

B. Preprocessing

Its primary goal is to enhance the usability of the data, ensure consistency, and simplify its representation for efficient analysis.

1) *Image Format Conversion*: The dataset's initial images, stored in TIFF format (.tif), are converted to JPEG format (.jpg) using the GDAL (Geospatial Data Abstraction Library) and Rasterio libraries in Python.
2) *Resolution Adjustment*: It involves adjusting the resolution of the images to a standardized size of 1074 x 984 pixels and it is essential for achieving uniformity across the dataset.
3) *Grayscale Conversion*: The dataset undergoes conversion to grayscale format during preprocessing to simplify the dataset by reducing the complexity of input images while retaining essential information for analysis.

C. Cloud Detection

It involves a systematic process to identify and analyze cloud formations for various applications, ranging from meteorology to environmental monitoring. The process begins with the conversion of INSAT satellite images into JPG format, followed by manual annotation to identify distinct cloud portions. Analyzing multiple images revealed three major cloud portions. The annotation focused on selecting custom regions within the images, designating highly white portions as clouds. The methods used include:

1) Mask RCNN (MRCNN)

It is a supervised segmentation network built on the ResNet architecture. ResNet, known for overcoming the vanishing gradient problem in deep networks, provides a robust foundation for the Mask RCNN model. COCO (Common Objects in Context) weights are used for the fine-tuning of the model. These weights have been trained on millions of images. The model has been trained and run for 10 epochs at a 0.001 learning rate, generating segmented images with colored, marked cloud regions, as seen in Figure 3.1.

Fig 3.1 Cloud Masking

2) K-Means Clustering

It is applied, in parallel, to the converted JPG image, treating it as a series of pixels. The features of each pixel, including the entropy, mean, and standard deviation (SD), are calculated considering its eight neighboring pixels. The K-Means clustering algorithm takes these feature vectors as input, with the number of clusters (k) assigned as 6. Its output is a thorough identification of all the cloud regions (both large and small) by the flood-fill method.

The result is visible in Figure 3.2, where there exists a detailed segmentation of cloud masses, enhancing the overall understanding of cloud patterns within the INSAT satellite imagery.

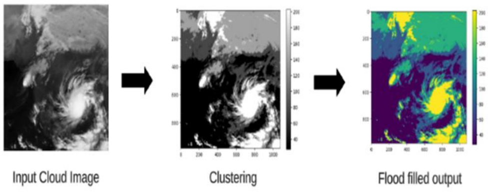

Fig 3.2 K-Means Clustering

D. Cloud Nowcasting

It is the prediction of imminent weather conditions within a short time frame and is crucial for various applications such as navigation, agriculture, aviation, and disaster management. In this context, the integration of advanced techniques, namely Mean Path Adjustment and Convolutional Long Short-Term Memory (Conv-LSTM) for predictive analysis, offers a robust solution for cloud nowcasting using INSAT satellite imagery:

1) MPA

It is a pivotal component in predicting cloud movements within the domain of cloud detection and motion forecasting. This methodology leverages the concept of the Center of Mass (CoM) to anticipate the trajectory of clouds across sequential images.

2) CNN-LSTM

It is a form of recurrent neural network that specializes in detecting time-related relationships among sequential information, making it suitable for time-series prediction problems. For cloud nowcasting, the Conv-LSTM model takes a series of segmented cloud images as input and learns the temporal evolution of cloud patterns over consecutive time intervals, as obtained in Figure 3.3. This understanding enables the model to predict the positions of identified cloud regions, with a focus on short-term forecasts.

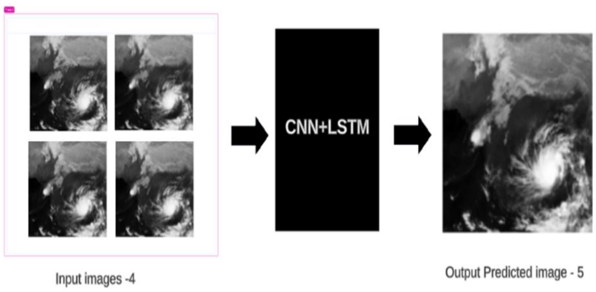

Fig 3.3 Conv-LSTM

IV. PROPOSED SYSTEM

The system architecture is meticulously crafted to ensure the seamless integration of different modules, fostering a cohesive and responsive web application. At the forefront is the User Interface (UI), serving as the sailor's gateway to interact with the system. The Cloud Detection Module, housing Mask RCNN, and K-Means Clustering algorithms, operates as a pivotal component, receiving input images from sailors and delivering cloud detection results. The Cloud Nowcasting Module integrates Conv-LSTM networks and functions by receiving a sequence of images from the Cloud Detection Module, producing forecasted images that offer insights into the anticipated cloud positions. The proposed idea of the system is depicted in Figure 4.1.

1) User- Interface (UI): It serves as the front end of the system, facilitating user interaction. Sailors can upload satellite images, view cloud detection results, and access predictions through an intuitive and responsive interface. It acts as the primary point of interaction between the system and the user, ensuring a user-friendly experience.

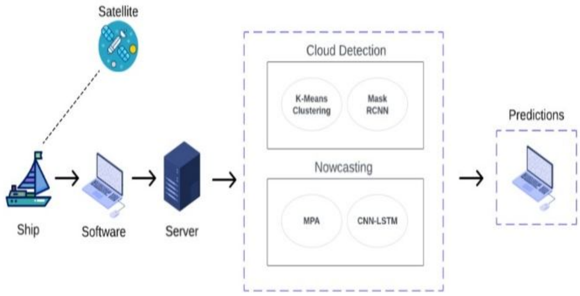

Fig 4.1 System Architecture

2) Cloud Detection Module: At the core of the system architecture is the Cloud Detection Module, where Mask RCNN and K-Means Clustering algorithms are implemented. This module receives input images from sailors through the UI and outputs the detection results.

3) Cloud Nowcasting Module: It is seamlessly integrated into the architecture, utilizing Conv-LSTM networks for cloud movement prediction. This module receives a sequence of images from the Cloud Detection Module, generating forecasted images, in the form of a GIF.

4) Backend Server: It acts as a pivotal component, managing the communication between the front-end UI and various modules. It coordinates the flow of data between modules, ensuring timely responses to user requests. The backend server is critical to the overall responsiveness and operation of the web application.

5) Database: A dedicated database is incorporated into the system architecture to store sailor data, historical cloud detection results, and prediction outcomes. The database facilitates data retrieval for analysis and reporting, contributing to the system's ability to provide sailors with valuable insights that help them choose the ship route.

V. Results And Discussion

The outputs obtained from the various modules express an idea about future weather conditions. The images are obtained from the INSAT-3D satellite every 30 minutes and passed to the Detection module for masking. Then, it is processed by the Prediction Module to generate 1 output image from a sequence of 4 input satellite images. When the connection between ship and satellite breaks, the images obtained are passed through the software, to generate an output GIF. It displays a visual representation of the predicted cloud motion and is much easier to understand.

The UI of the landing page is presented in Figure 5.1. The uploading of cloud image for Cloud Masking is performed in Figure 5.2.

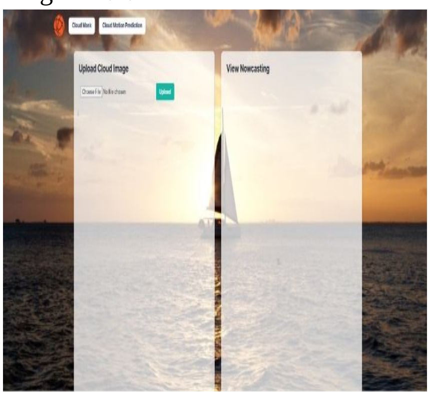

Fig 5.1 UI

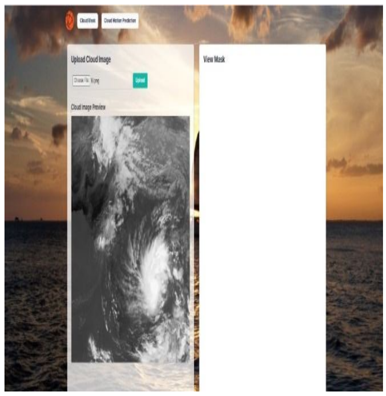

Fig 5.2 Image upload for Cloud Masking

On selecting the Upload button, the Cloud Mask is displayed, as seen in Figure 5.3. The uploading of cloud image for Cloud Nowcasting is performed in Figure 5.4

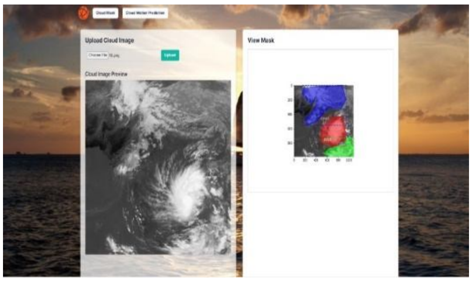

Fig 5.3 Cloud Mask is obtained

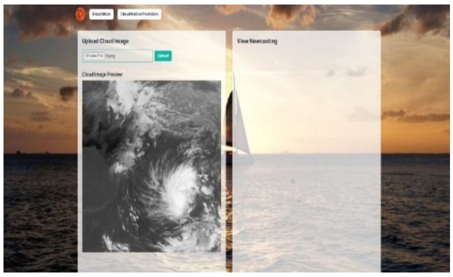

Fig 5.4 Image upload for Nowcasting

On selecting the Upload button, the predicted cloud motion is displayed as a GIF, as seen in Figure 5.5.

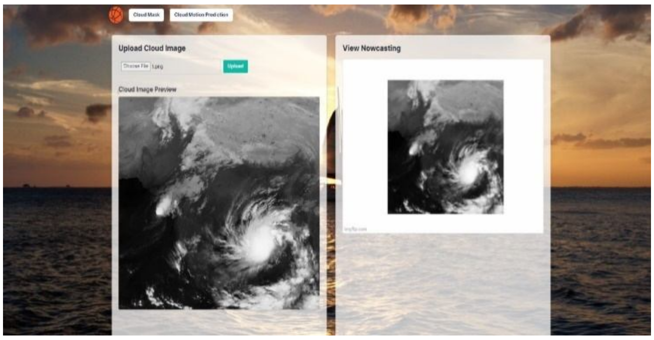

Fig 5.5 Output GIF

For Cloud Detection, the MRCNN method is chosen over K-Means Clustering due to faster computation, less memory, better accuracy, and the identification of the important cloud regions. The K-Means method identified all the clouds (small and large), that is, flood filling.

For Conv-LSTM, 4 models were tested to determine the number of input images to predict the output. The results are discussed in Table 5.1.

TABLE 5.1: INPUT-SIZE TUNING

Model	**Sequence Size**	**Input Image Size**	**Mean Squared Error**
1	4	300 x 300	2326.2891
2	4	150 x 150	2228.9563
3	15	300 x 300	3267.8962
4	15	150 x 150	3173.1775

So, Model 2 having input sequence size 4 for 150 x 150 sized images is chosen.

For the Max Pool size, the best output was obtained when the value was 4, as obtained in Figure 5.6. From Figure 5.7, it is observed that a Dropout Probability of 0.4 generated the best results.

	train	validation
MaxPool 2	7868.917969	6701.196289
MaxPool 3	7843.534180	6681.533691
MaxPool 4	7832.342773	6683.696289

Fig 5.6 Max Pool

	train	validation
Dropout 0.0	7863.664551	6715.783691
Dropout 0.2	7830.378906	6674.964844
Dropout 0.4	7801.705078	6647.786621
Dropout 0.6	7812.050293	6665.425781

Fig 5.7 Dropout Probability

The proposed system utilizes 1024 LSTM units, as validated from Figure 5.8. The Activation Layer of SoftPlus generates high accuracy and low training loss, as observed in Figure 5.9.

	train	validation
LSTM 128	12719.527344	11534.010742
LSTM 256	11559.324219	10450.892578
LSTM 512	9616.114258	8673.856445
LSTM 1024	6884.819336	6259.774414

Fig 5.8 No. of LSTM Units

	train	validation
Activation None	6895.440918	6267.247070
Activation Relu	9228.008789	8403.231445
Activation Softplus	6772.929199	6159.087402

Fig 5.9 Output Layer Activation

From Figure 5.10, it is evident that the nadam Model Optimizer generates the best, low error results.

	train	validation
Optimizer sgd	13903.940430	12641.008789
Optimizer rmsprop	6992.922363	6372.478516
Optimizer adam	6895.540527	6266.379883
Optimizer nadam	6758.768555	6156.857422
Optimizer adamax	7948.575195	7236.729004

Fig 5.10 Model Optimizer

VI. Conclusion And Future Enhancement

The research has successfully addressed the challenge of ship navigation during the loss of connection by the amalgamation of state-of-the-art methodologies, including MRCNN, Conv-LSTM, and MPA. A high Similarity Index of 0.8363 is obtained. The sailors view the output GIF of nowcasting, thereby helping them in re-routing the ship accordingly. Its results can be improved by access to real-time data and the addition of more testing images.

References

[1] Mahajan, S., & Fataniya, B. (2020). A comprehensive review of cloud detection methodologies - variants and development. https://doi.org/10.1007/s40747-019-00128-0

[2] Sun, Lin, et al. "A universal dynamic threshold cloud detection algorithm (UDTCDA) supported by a prior surface reflectance database." Journal of Geophysical Research: Atmospheres 121.12 (2016): 7172-7196.

[3] Reiter, Philippe. “Cloud Detection through Wavelet Transforms in Machine Learning and Deep Learning.” ArXiv abs/2007.13678.

[4] Shao, Zhenfeng, et al. "Cloud detection in remote sensing images based on multiscale features-convolutional neural network." IEEE Transactions on Geoscience and Remote Sensing.

[5] Huang, W, Wang, Y, Chen, X. Cloud detection in high-resolution remote-sensing images of urban areas using color and edge features based on dual-color models (2018). International Journal of Remote Sensing.

[6] Julia Amorós-López, Luis Gómez-Chova, Jordi Muñoz-Marí, Gonzalo Mateo-García, Gustau Camps-Valls. Cloud masking & removal by Remote Sensing, Vol. 11, Issue 1, 01505 (January 2017). doi.org/10.1117/1.JRS.11.01505

[7] Cheng G , Xie X, Han, J ,Wang J, Yao X,. (2021). Proceedings of the I.E.E.E/C.V.F International Conference on Computer Vision (I.C.C.V) .

[8] Piotr Dollár, Georgia Gkioxari, Kaiming He, Ross Girshick. “Mask RCNN”, 2017 I.E.E.E International Conference on Computer Vision. DOI: 10.1109/ICCV.2017.322.

[9] Shaoqing Ren, Kaiming He, Ross Girshick, Jian Sun. Faster R-CNN: Towards real-time object detection with region proposal networks. In “Advances in neural information processing systems”.

[10] Kaiming He, Shaoqing Ren, Ross Girshick, Jian Sun. "Prediction of Short-Time Cloud Motion Using a Deep-Learning Model.".

[11] Zhiying Lu, Zehan Wang ,Xin Li , Jianfeng Zhang (2021).Cloud motion prediction using CCLSTM+ SR-Net.

[12] Ye, Maosheng, Tongyi Cao, and Qifeng Chen. “TPCN”: Temporal point cloud networks for motion forecasting." ,Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2021.