IJCSE International Journal of Computer Sciences and Engineering Open Access
Research Paper Vol.-7, Issue-7, Jul 2019 E-ISSN: 2347-2693

Deep Learning Technique for Cloud Detection using Satellite Data

Dhrupa Patel[1*], Sonal Rami[2]

[1]Dept. of Information Technology, Chandubhai S Patel Institute of Technology, CHARUSAT University, Nadiad, India
[2]Dept. of Information Technology, Chandunhai S Patel Institute of Technology, CHARUSAT University, Nadiad, India

**Corresponding Author: dhrupapatel337@gmail.com, Tel.: (+91) 8140123307*

DOI: https://doi.org/10.26438/ijcse/v7i7.3339 | Available online at: www.ijcseonline.org

Accepted: 15/Jul/2019, Published: 31/Jul/2019

***Abstract*— Cloud detection is a crucial task and has varied ranges of implications in retrieving important parameters using satellite data. Identifying clouds from clear sky hold great importance in many satellite Imagery applications. Many approaches are used for performing cloud detection on satellite data products. Some of the well-known approaches are a threshold-based approach, a machine learning approach, and a few others, but these approaches lack robustness as these approaches require a profuse amount of time in performing feature-selection. Most of the algorithms fail in taking advantage of spatial arrangement and are time intensive. In tasks like image recognition and object detection, deep learning has outperformed compared to other approaches. In this paper, a deep learning model was proposed for performing cloud detection using INSAT 3D satellite data product which overcomes all the above-mentioned limitations. The proposed model architecture consists of encoder and decoder modules, which will perform sampling, feature extraction, and up-sampling. The proposed model takes five features consisting of SWIR, VIS, TIR1, TIR2, and MIR spectral band's/channel's data as input and generates cloud mask as output. Generated cloud mask performs better distinction between cloudy and non-cloudy pixels under different surface conditions, mostly over ice and snow. The proposed model will generate a day-time cloud mask as SWIR and VIS spectral bands data are available only during the day-time.**

***Keywords*—** Deep Learning, Cloud detection, Multispectral channels, Satellite data, INSAT 3D.

I. INTRODUCTION

Cloud retrieval is an important task in satellite Imagery applications. "Detecting cloud using satellite imagery has a plethora of important applications in weather and climate studies."[1]. "Cloud information is also important for managing energy grids since cloud coverage influences the spatial and temporal availability of solar power." [2] Furthermore, "clouds are indicators for global and local weather conditions. They occur in extreme weather events such as storms and heavy rainfall that can cause severe damages and threaten human life." [3] Thus we need a mechanism which can accurately identify presence and locality of cloud in cloud-contaminated satellite data product. One of the approaches used for cloud detection is, Classical machine learning approach for identifying clouds in satellite imagery, requires explicit features extraction for training the model. Different machine learning algorithms are used for different satellite data products. Authors proposed the spatial procedures for automated removal of the cloud and shadow (SPARCS) algorithm for Landsat scenes, which uses neural network for cloudy and non-cloudy classification. "This development was motivated by the need for efficient and reliable cloud and cloud shadow masking in a forest change detection application over highly heterogeneous land cover in the eastern U.S.; existing methods were either too computationally intensive or missed many clouds or cloud shadows, which were detected" [4] Yuan, Yi, and Xiangyun Hu (2015) proposed bags-of-words model for overcoming the highly varying patterns of clouds, which segments the images into super-pixels and applied an SVM to classify cloudy and non-cloudy regions [5]. The author used the SVM classification of cloudy and non-cloudy regions for MODIS data [6] [7]. Deep Learning models had outperformed in image recognition, object detection, and much more complex task compared to state-of-art-methods. In current studies, deep learning is used for performing cloud detection in satellite imagery. Deep Learning model consists of many convolutional layers stacked up, which performs feature extraction. Thus deep learning is preferred over machine learning algorithm as it doesn't require explicit identification of features, which is considered as cumbersome and time-consuming task. “The Simple convolutional neural network (CNN) architecture was designed for the cloud masking of Proba-V multispectral images.”[8]. In the paper, “Multilevel cloud detection in remote sensing images based on deep learning” a model was proposed which uses an adaptive simple linear iterative clustering (A-SCLI) algorithm which segments high-resolution satellite images to superpixels. Later “a new multiple convolutional neural networks (MCNNs) architecture is designed to extract multi-scale features from each superpixel, and the superpixels are marked as thin cloud, thick cloud, cloud shadow, and non-cloud”. “Three categories of different spatial resolutions satellite imagery, GaoFen-1 (GF1), GaoFen-2 (GF-2), and ZiYun-3 (ZY-3), were used for multilevel cloud detection.”[9]. A deep learning model was proposed for performing distinction between cloud and snow using Gaofen satellite images [10]. The experimental results suggested that deep convolutional neural network have promise for solving cloud masking problems, compared to the classical machine learning approach and have accurately generated cloud mask for INSAT 3D satellite.

This paper is organized as follows, Section I contains introduction about the importance of cloud detection and various existing approaches used for specific satellite data, Section II consists of related work about why deep learning is better solution than other approaches, Section III delineate about the methodology used for attaining the problem specified consisting of dataset specification, algorithm and implementation strategy used, Section IV is results and discussions which presents the results obtained from proposed model and based on results discusses about the discrimination of cloudy and non-cloudy pixels, Section V concludes research work carried out and bounds the scope of the proposed model.

II. RELATED WORK

There are various approaches which can be used for achieving cloud detection task. Some of the techniques used for other satellite data products for performing cloud detection task are:

- Rule-based classification based on the physical properties of clouds.
- Super-segmented pixel and SVM
- Neural Network for performing cloud detection
- Traditional Threshold-based classification

Most probably threshold-based and machine learning approaches are used for performing cloud detection using satellite data products. Three drawbacks of threshold-based and classical machine learning algorithms which can be ruled out by using a deep learning approach. Threshold-based and classical machine learning algorithms decide whether an individual pixel is cloudy or cloud-free avoiding spatial information that doesn’t limit to adjacent pixels. As the clouds are spatially continuous and dynamic, thus for achieving better performance spatial information is essential. Some algorithms do consider spatial information in proximity of (3*3) pixels region whereas a deep learning algorithm takes advantage of all available spatial information. Products derived from satellite data are generally used for forecasting or nowcasting and the analysis process. Thus cloud mask generation should take hardly a few seconds. In classical machine learning algorithm and threshold-based algorithm, feature selection is quite an essential part, requiring a bountiful amount of time and also is very cumbersome task whereas deep learning algorithm has automated feature selection capability. Thus in our work, we have used deep learning approach for transcending above mentioned limitations of other approaches for performing cloud detection using satellite data product.

III. METHODOLOGY

Deep learning is a subfield of machine learning with some exciting and novel features. We have proposed a deep learning model for performing cloud detection using satellite data products. The cloud detection process was carried out using the L1B standard data and its corresponding cloud labels data of INSAT-3D satellite. The standard data consists of various spectral bands; each band holds different wavelength values. In this paper, we are going to use five spectral bands data for differentiating cloudy and non-cloudy pixels under different surface conditions taking advantage of the difference in reflectance value of different types of clouds. For generating a cloud mask, segmentation was performed. First, the clouds were detected and then cloudy regions were segmented from non-cloudy regions. The proposed deep learning model consists of convolutional layers, deconvolutional layers with some regularization technique for achieving better performance. The proposed deep learning model takes five features as input and as an output, it will generate a probability mask. The five features are different spectral bands data of different resolutions, used for achieving better performance. In the proposed model, each spectral band is processed individually and later the processed inputs are merged while training and testing the model. As shown in Figure 1, the flow chart of the proposed model is made up of two stages: model training and model testing. The probability mask will be further manipulated for segmenting cloudy and non-cloudy regions.

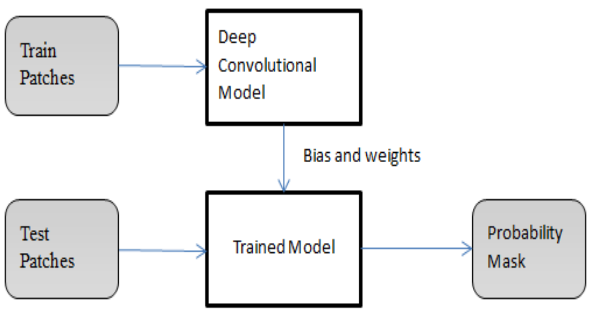

Figure1. Flow chart of the proposed model

1) Dataset

Dataset was created using INSAT 3D satellite data product. Table 1, depicts the multi-spectral channels used in creating the dataset. As specified in Table 1, each spectral channel/ band has different resolution values. The data of different resolution were brought to 4 km resolution using data preprocessing technique, for bringing 1 km resolution to 4 km resolution the data were averaged. For our proposed model, SWIR, MIR, TIR1, TIR2 and VIS channel data were taken into consideration. As for performing cloud detection satellite data products was used, the dimension of each data was quite high which limits the processing power and memory limit of an experimental system on which experiment was carried out. For overcoming the resource limitation, a data patch of (200 × 200) dimension was selected for processing. The dataset created using data patches includes the dynamic ranges of data. The training and testing dataset were created using (200 × 200) dimension data patch from each channel, resulting in input to a model consisting of five (200, 200) data patch. The patches can be clipped to any size 255 × 255, 512 × 512, etc. according to processing speed and memory limit of the experimental system.

TABLE 1
PAYLOAD SPECIFICATION OF INSAT 3D IMAGER

Spectral Channels	Spectral Range (μm)	Resolution
Thermal Infrared-1(TIR-1)	10.3-11.3	4 km
Thermal Infrared-2 (TIR-2)	11.5 –12.5	4 km
Midwave Infrared (MIR)	3.80-4.00	4 km
Shortwave Infrared (SWIR)	1.55-1.70	1 km
Visible (VIS)	0.55–0.75	1 km

2) Algorithm

Deep Convolutional model was created for performing cloud detection. Figure 2, depicts the architecture of the proposed model. Below mentioned steps are the algorithm used for generating a cloud mask using the proposed model.

- Step 1: Data patch of (200*200) dimension was pre-processed; spectral band's data of different resolutions were brought to a common resolution.
- Step 2: Training and the testing dataset was created using above pre-processed data and stored in numpy file format.
- Step 3: As shown in the below figure, the model is stacked up with different layers which takes five spectral band data as input and generates a single output of the same size as that of input.
- Step 4: Each input is passed through a convolutional layer for performing feature extraction.
- Step 5: After passing through the convolutional layer the resultant output is passed to batch normalization and dropout layer for reducing the training time and avoiding Overfitting or instability in a network.
- Step 6: Another convolutional layer with an increase in the number of filters and batch normalization layer are stacked up, for the further feature extraction process, so that only important features are taken into consideration.
- Step 7: After extracting features, a deconvolutional layer was used for getting output the same size as that of input.

- Step 8: Each input undergoes step 4 to step 7 (As shown in Figure 2) and at the last stage all the processed features are merged using the Merge layer.
- Step 9: The output of the Merge layer is passed to the convolutional layer for generating a probability mask. This convolutional layer has filter size (1*1) as each pixel is assigned two probability values, one is a probability of pixel is cloudy and the other holds the probability of pixel is non-cloudy.
- Step 10: The probability mask is used for generating a cloud mask.

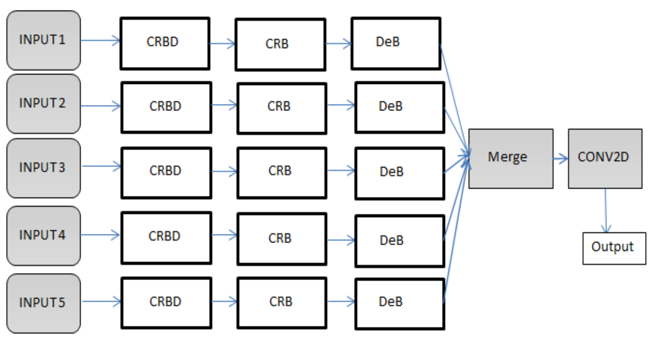

Figure 2. Proposed deep convolutional model for generating a cloud mask using INSAT 3D Satellite Data Product.

INPUT1: Thermal Infrared-1 (TIR-1)
INPUT2: Thermal Infrared-2 (TIR-2)
INPUT3: Midwave Infrared (MIR)
INPUT4: Shortwave Infrared (SWIR)
INPUT 5: Visible (VIS)

CBRD: Convolutional2D Layer + Batch normalization Layer + Dropout Layer.
CRB: Convolutional2D layer + Batch Normalization Layer.
DEB: Deconvolutional2D Layer + Batch Normalization Layer.

3) Implementation Strategy

The satellite data were stored in the HDF5 file format. HDF5 file format is one of the acknowledged file formats by WMO (World Meteorological Organization) for exchanging and storing meteorological data. For creating training and testing dataset according to the requirement specified in dataset segment, h5py library of python was used for retrieving and manipulating the HDF5 file format data. The proposed model consists of encoding and decoding layers. Various other parameters were tuned for providing proper training. The model was trained with Adam optimizer. Various callbacks function like ReduceLROnPlateau function, which monitors val_loss with patience value set to 5; if model stops learning the learning rate is reduces by factor 0.2 till 0.0001 learning rate and another ModelCheckpoint function were used which stores weights and bias value when val_acc turns out to be maximum. Some of the layers used for creating a deep convolutional neural network are delineated below.

Conv2D Layer: Conv2D is used for creating a convolutional layer of n number of filters (nodes) with k*k as a filter size. The input shape to the convolutional layer is (h, w,c), where h and w is height and width of input feature array with c as the number of channels. The output of the feature map would be $h' * w' * n$. The ith feature map yi can be found out using the equation:

$$y_i = w_i \times x_i + b_i \qquad (1)$$

In Equation (1), w_i and b_i are the i^{th} weights and i^{th} bias with x_i as i^{th} input feature map. The convolutional layer (Conv2D) has used the Rectified linear unit (Relu). Equation of Relu activation function is:

$$f(x) = \max(x,0) \qquad (2)$$

The input shape was clipped to (200, 200, 1) and filters of size (3×3) were used. Figure 3, provides a clear view of how features are extracted using kernel/filter from the provided image array.

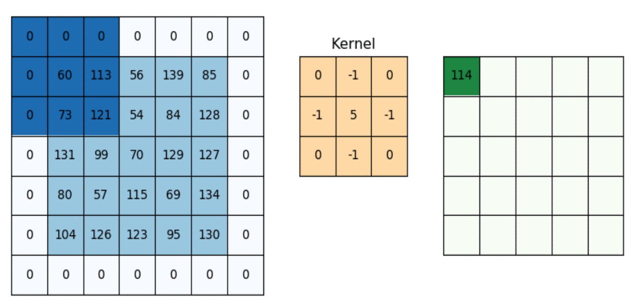

Figure 3. The figure shows the processing of the conv2d layer with (3×3) filter size.

Conv2DTranspose: Conv2DTranspose is Transposed convolution layer also called as deconvolutional layer. This layer will result in generation of cloud mask as the same size as that of input shape. The Conv2DTranspose uses the same values of strides, filter size and number of filters as that of used for Conv2D layers (as perform the deconvolutional operation) but the number of filters is taken in reverse order as that of Conv2D layer.

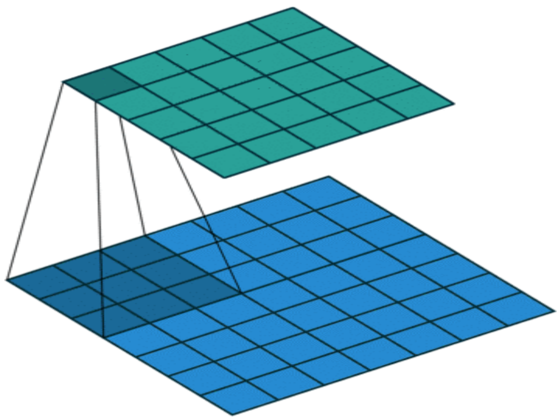

Figure 4. Insight about how the deconvolutional layer works.

Dropout: The term Dropout itself explains its meaning, dropping out something. In terms of the convolutional neural network, dropout refers to dropping out neurons in the training phase. It is one of the regularization techniques for avoiding Overfitting. In the training phase (1−p) % of the neuron will be used and p% of neurons will be removed in each epoch. Here p value is in range of (0-1). Below shown figure 3 will give you a clear understanding of how dropout works. In our proposed model, we have applied 20% of dropout it means 20 neurons or nodes will be removed out of 100 neurons or nodes for providing proper learning.

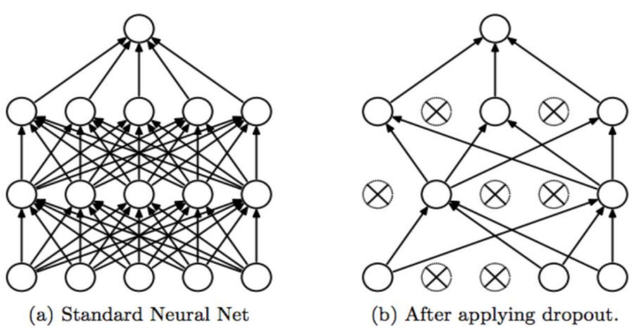

Figure 5. Dropout layer for avoiding Overfitting

Batch Normalization: Generally Batch Normalization is used for reducing training time and elude the instability in the network due to large value difference in features. This layer is normally placed after layer, whose values we want to normalize for avoiding instability while cascading through the network. Following are steps performed by batch normalization layer:

1. It normalizes the output obtained from the activation function.

$$z= (x-m)/s \tag{3}$$

2. The obtained value is multiplied by arbitrary parameter, g.

$$z= z\times g \tag{4}$$

3. The obtained value is added with another arbitrary parameter, b.

$$z= z+b \tag{5}$$

Here m, s, g, and b are trainable parameters that get optimized with training.

IV. RESULTS AND DISCUSSION

The proposed deep convolutional model was trained and tested using varied seasons of data. The training dataset made up of INSAT 3D data product, which is generated every half-hourly. The training dataset consists of patches, which cover land, ocean, cloud, forest and many more surface so that the model can accurately distinguish cloudy and non-cloudy pixels under varied surface conditions. The model was tested using INSAT 3D cloud properties data product, which is another operational data products. The testing dataset also consists of various months' data, such that every season's data is validated. Below shown are some of the resultant patches obtained while passing the testing dataset to the trained model. It is quite evident from below figures that the generated cloud mask provides a punctilious distinction between cloudy and non-cloudy pixels taking advantage of available channels. The Generated cloud mask consists of two colors: white pixel represents cloudy pixel whereas black pixel represents a non-cloudy pixel. Different channels radiance values were mapped to gray scale, such that through figures one can evaluate the results obtained.

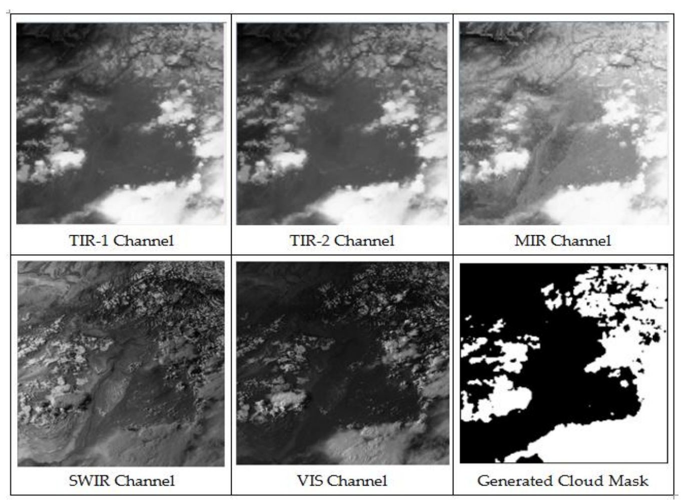

Figure 6. Test Data-1 (3DIMG_21JUL2018_1130). Latitude, Longitude of left lower corner: 28.3 67.93 and upper right corner: 37.64 75.71

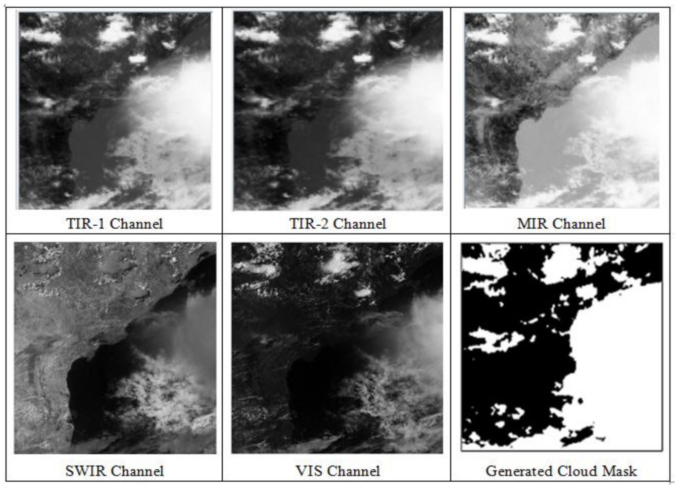

Figure 7. Test Data-2 (3DIMG_20JUN2018_0830). Latitude, Longitude of left lower corner: 12.44 78.21 and upper right corner: 20.15 85.76

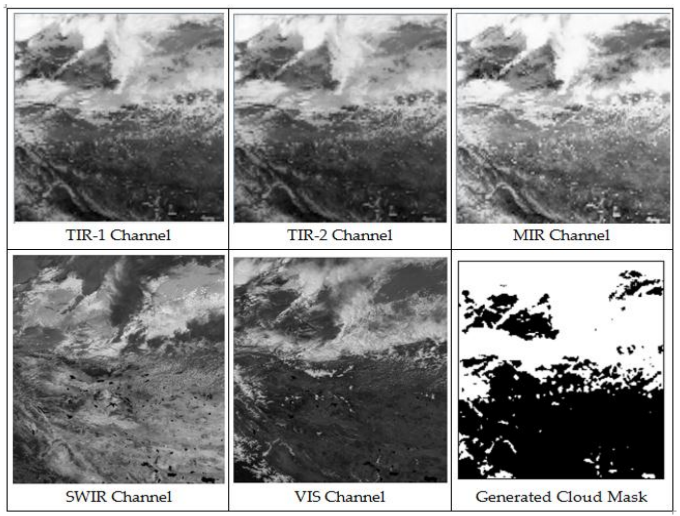

Figure 8. Test Data-3 (3DIMG_20MAY2018_0730). Latitude, Longitude of left lower corner: 30.85 77.61 and upper right corner: 40.85 86.81

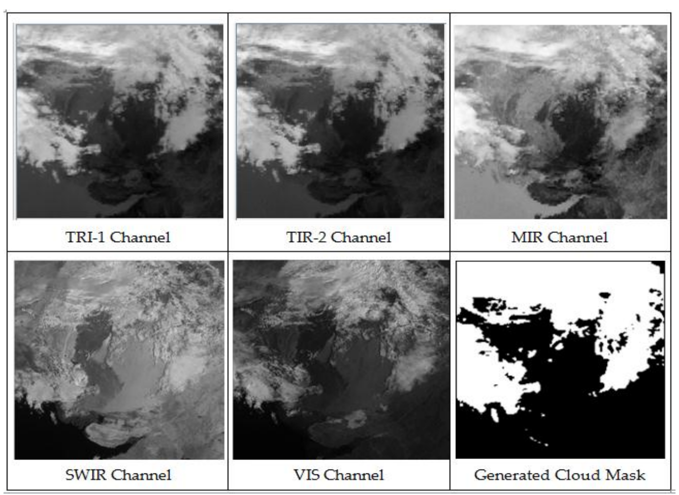

Figure 9. Test Data-4 (3DIMG_01MAR2019_0430). Latitude, Longitude of left lower corner: 22.38 65.81 and upper right corner: 30.86 73.22

Clouds are normally identified because of their higher reflectance and lower temperature than the underlying earth surface, but there are some conditions in which the distinction of clouds becomes difficult, most probably over snow and ice. Most of the algorithms used for performing cloud detection task, merely able to take advantage of all available spectral bands data. In this paper, the deep learning model takes advantage of all available spectral information for performing the proper distinction of a cloudy and non-cloudy pixel. The proposed model was tested on dynamic ranges of patches, and later the patches were combined to generate a complete cloud mask. Using latitude and longitude values, a cloud mask for INSAT 3D Imager data product was generated, consisting of different surface conditions. The proposed model needed to be evaluated, for verifying its performance in the cloud detection task. The model was trained for 30 epochs with 93% as training accuracy. Best weights and bias were stored in HDF5 file format, which was further used for generating the cloud mask for unknown data.

For validating the model INSAT 3D cloud properties data product was used. INSAT 3D cloud properties data product consists of the various attribute which implicates the presence of cloud. INSAT 3D cloud properties data product information is bounded to the ASIA region, thus various patches of the INDIAN region were used for validating the trained model. Cloud Phase attribute of cloud properties data product was taken into account for generating cloud labels for validation.

The accuracy determines the accordance and discordance of the generated cloud mask with the cloud mask generated using INSAT 3D cloud properties data product. For validating generated cloud mask 48 different patches of months January, February, March, May, July, June, December of day-time were validated using INSAT 3D cloud properties data product. The overall testing accuracy turned out to be 81.05%, which shows the capability of model in performing cloud detection using INSAT 3D satellite data product. Here 81.05% determines the percentage of pixel value matched with validation data.

V. CONCLUSION AND FUTURE SCOPE

The model was proposed for performing cloud detection task for INSAT-3D Satellite data. Introduction section mentions various deep learning model proposed by authors but those deep learning models cannot be implemented for INSAT-3D data product due to difference in resolution value and spectral bands of INSAT-3D satellite with other satellite data product. Results provided in results and discussion section implicates that proposed model performs better in discriminating a cloudy and non-cloudy pixel. The proposed model is limited for day-time payload as proposed model takes into account SWIR and VIS spectral bands that are only available during day-time (IST).

REFERENCES

[1] Jedlovec G., "*Automated detection of clouds in satellite imagery*"; In Advances in Geoscience and Remote Sensing, IntechOpen, 2009.

[2] Köhler C.; Steiner A.; Saint-Drenan YM.; Ernst D.; Bergmann-Dick A.; Zirkelbach M.; Bouallègue ZB.; Metzinger I.; Ritter B.; "*Critical weather situations for renewable energies*"–Part B: Low stratus risk for solar power. Renewable energy **2017**, 101, 794-803.

[3] Drönner J.; Korfhage N.; Egli S.; Mühling M.; Thies B.; Bendix J.; Freisleben B.; Seeger B. "*Fast cloud segmentation using convolutional neural networks*". Remote Sensing **2018**, *10*, 1782.

[4] Hughes M.; Hayes D.; "*Automated detection of cloud and cloud shadow in single-date Landsat imagery using neural networks and spatial post-processing*". Remote Sensing, **2014**, 6, 4907-26.

[5] Yuan Y.; Hu X.; "*Bag-of-words and object-based classification for cloud extraction from satellite imagery*". IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, **2015**, 8, 4197-205.

[6] Bai T.; Li D.; Sun K.; Chen Y.; Li W.; "*Cloud detection for high-resolution satellite imagery using machine learning and multi-feature fusion*". Remote Sensing, **2016**, 8, 715.

[7] Ishida H.; Oishi Y.; Morita K.; Moriwaki K.; Nakajima TY.; "*Development of a support vector machine based cloud detection method for MODIS with the adjustability to various conditions*". Remote Sensing of Environment, **2018**, 205, 390-407.

[8] Mateo-García G.; Gómez-Chova L.; Camps-Valls G.; "*Convolutional neural networks for multispectral image cloud masking*". In 2017 IEEE International Geoscience and Remote Sensing Symposium (IGARSS), **2017**, pp. 2255-2258, IEEE.

[9] Xie F.; Shi M.; Shi Z.; Yin J.; Zhao D.; "*Multilevel cloud detection in remote sensing images based on deep learning*". IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, **2017**, 10, 3631-40.

[10] Zhan Y.; Wang J.; Shi J.; Cheng G.; Yao L.; Sun W.; "*Distinguishing cloud and snow in satellite images via deep convolutional network*". IEEE Geoscience and Remote Sensing Letters, **2017,** 14, 1785-9.

Authors Profile

Ms. Dhrupa Patel pursued a Bachelor of Technology in Information Technology from Charsuat University, Changa, Anand in 2019.

Ms. Sonal P. Rami is working as an Assistant Professor at the Department of Information Technology in Chandubhai S Patel Institute of Technology, CHARUSAT since June 2014. She received the Bachelor degree in Information Technology from C. U. Shah College of Engineering & Technology in June 2010. She got a master's degree in Computer Science & Engineering from Kalol Institute of Technology & Research Centre in September 2013. In her 09 years of a teaching career, she has developed subject proficiency in Machine Learning, Deep Learning, Python Programming, Artificial Intelligence, Data Structures, and Design & Analysis of Algorithm. She taught the students at UG and PG levels. Her research area is in Machine Learning, Deep Learning, and Computer Vision. She has published 17 research papers in national and international journals also a member of the Computer Society of India and appointed as a faculty sponsor of CHARUSAT ACM Student Chapter-Association for Computing Machinery. She is a member of the Training & Placement Committee of the Department of Information Technology at CSPIT, CHARUSAT.