

Cloud Classification using Satellite Imagery and Deep Learning

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Abstract— On going advancements in remote sensing (RS) technology have made a substantial amount of satellite image data available for various applications. Cloud cover, a major issue on many regions on Earth surface, impedes the acquisition of valuable Earth observation data by optical satellite imaging systems and adversely impacts the processing and utilization of optical satellite images. Because of the growing interest in remote sensing and deep learning, cloud detection has become a crucial preprocessing step in preparing optical satellite images for operational systems. Deep learning needs massive data. Transfer learning methods are found as an efficient solution accurate categorization of satellite images with limited dataset. This work presents an integrated strategy comprising the transfer learning based InceptionV3 pre trained model as a feature extractor and Random forest as an ensemble learning based classifier. This study proposes Sentinel-2 optical satellite imagery based new dataset CloudS2 dataset, which has two classes and hundreds of high-resolution images. The proposed model works effectively on limited dataset further improving the network's performance. The proposed model employs the newly built CloudS2 dataset and classifies images into respective classes. The InceptionV3-RF model outperforms the existing deep learning-based models such as VGG-16, MobileNetV2, Xception, DenseNet201 and InceptionResNetV2 and achieves an overall accuracy of 86.6%. The proposed research work is useful as a preprocessing stage in deep learning applications applied to remote sensing optical satellite imagery.

Index Terms— Remote sensing, Deep learning, Transfer learning.

I. INTRODUCTION

Remote sensing, a way of acquiring information about physical characteristics of object using from distance typically with aircraft or satellite sensors. The satellite based passive sensor and active sensor technologies are prominently used to acquire earth observation data. The satellite sensors provide data in various spatial and temporal resolutions. Further this earth observation data is utilized for various applications like Agriculture, Disaster management and commercial sectors. Optical satellite imagery data acquired from optical satellite sensors is better for interpretation. However, it is highly affected by cloud cover. During rainy season it is most of the area on earth surfaces is covered with cloud either dense or sparse. The presence of cloud in satellite image poses limitations on observations of objects on earth surface as it blocks landscape scenes. It hinders the spatial analysis of crop land [22], urban areas and other objects on Earth surface [23]. Therefore, it is essential to detect and remove

the cloud from satellite imagery for rigorous analysis. The conventional methods of cloud classification are based on thresholding method. The method considers some threshold value. The pixels ratio above threshold value is labeled as cloud and the ratio below threshold values referred as sky. The split window method and statistics-based method are also utilized for cloud classification task. These methods perform cloud classification but with its own set of limitations. These methods may fail in certain cases due to complexity [7]. In past few decades, Machine learning is widely being used for earth observation data. Supervised and unsupervised machine learning methods are typically used for cloud classification. From the related literature, it is evident that, researchers have utilized various methods of supervised machine learning techniques like support vector machine [22], Bayesian classifier [1] [2], Multi category SVM [3], K-neighbor and neural network for cloud classification [4] from satellite imagery. Few studies have explored the unsupervised leaning approach with K-Means algorithm. The conventional machine learning methods need feature engineering before it is applied to satellite imagery. A domain expert is required for extract the appropriate features. The aforementioned issue is taken care by deep learning. Advances in infrastructure have created the new ways of utilization of deep learning for earth observation data. In last decade, deep learning methods have shown remarkable success on earth observation data for various remote sensing applications. The deep supervised and unsupervised learning methods are adapted for cloud detection. The representative deep learning architectures such as Convolution neural network [5] [6], Recurrent neural network, Generative adversarial network and deep belief networks are adapted for cloud classification from satellite imagery. Few studies have utilized the combination of deep learning and machine learning to accomplish the aforementioned task. The clouds classification from optical satellite imagery is the topic of research since beginning. Lot of research is done and still there is scope for improvement. In this paper, attempt has been done to build deep learning model using transfer learning approach for feature extraction and random forest for cloud classification. The performance is evaluated with performance evaluation metrics.

The contribution of this paper is as follows:

1. Dataset CloudS2 is proposed with multi temporal multispectral satellite images for the task of cloud classification.
2. Pre trained models are used as a feature extractors and ensemble learning method is used for classification. Pre trained model helps to enhance the feature extraction with better accuracy.
3. Performance evaluation of various deep learning methods is done on CloudS2 dataset.

Following that, the rest of the paper is structured as follows: Section II presents a summary of related research. Part III describes the materials and methods of the proposed system. Section IV contains the results discussion and lastly, section V concludes the paper.

II. RELATED WORKS

Cloud classification from satellite imagery is essential for various operational systems. Various researchers have utilized the numerous methods for cloud classification. The typical methods include conventional methods, Machine learning based methods and recent deep learning methods. Conventional methods include methods like Thresholding method, Texture based method, split window method and statically methods applied on satellite imagery. These conventional methods are adapted by various researchers on numerous satellite sensor data such as LandsAT and MODIS. An RGB cloud image is converted to a feature image of single channel. The ratio of red channel to blue channel is computed. Fixed threshold value is further utilized to classify each pixel in the image. Numerous variations are implemented by researchers. For instance, Heinle et al. computed the difference between the red and blue channel instead of the R/ B ratio [8] and further utilized fixed threshold method. The fixed threshold methods are good. However, it has some challenges associated with it. Specifically, these methods are unable to detect thin clouds. Yang et al. 2009 utilized Ostu threshold algorithm based adaptive thresholding method for cloud detection. Though the method works well for cloud detection it does not work effectively for sky images. Qiugyong Li proposed a hybrid Thresholding algorithm that integrates the fixed threshold method with adaptive thresholding method for cloud detection and achieved the accuracy of accuracy of 88.53%. Though the threshoding methods and its variants provide good results they have some limitations. Machine learning is widely being used for remote sensing applications.

Support vector machine, Random forest, Naïve Bayes, K-Means and K-Nearest Neighbour algorithm are generally used for cloud classification. The methods are based upon features which are extracted manually. For instance, Wang et al. employed Random forest on Satellite Data from CloudSat and Himawari-8. In another study, Jiang, Y. et al. applied the semi supervised learning approach that combines support vector machine and K-Means algorithm for cloud detection.[7]. Method is good. However, similarity in pixel in spectral bands interfered with

random forest. Elsy Ibrahim [22] employed two stages Machine Learning method that can efficiently classify the images into cloud, cloud shadow and clear images. The classification accuracy of algorithms is impacted by type of features extracted. Deep learning has created great impact in remote sensing domain with its wide range of applications. Convolutional neural network can perform feature extraction automatically. For instance, Chen et al. implemented multilevel cloud detection algorithm based on CNN. Initially super pixels are clustered then they are provide too multiple CNN[11]. In another study, Tingting Zhu adopted transfer learning approach and performed cloud classification of cloud images using AlexNet, VGG16, Resnet18. It is observed that ResNet18 achieved 91% accuracy and outperformed the machine learning based methods [24]. Drönner et al. used UNet architecture on Meteosat satellite imagery to perform cloud detection and have shown the better performance.[12] Jacob Høxbroe Jeppesen et al. proposed a new method RS-Net for cloud detection from Optical satellite imagery LandSAT 8.[13].The method provides promising results. The results can further be improved with ensemble learning approach. To deal with this, Yousaf, Rukhsar et al. applied a new ensemble learning approach snapshot-based residual network (SnapResNet). The method is capable of handling interclass similarity problem and efficiently performs cloud classification with 97.25% accuracy [14]. While few researchers explored deep supervised learning methods for cloud classification and detection, other researchers explored unsupervised learning approach. For instance, Takuya Kurihana et al. proposed a framework that learns the cloud features from Moderate Resolution Imaging Spectroradiometer (MODIS) satellite data [15]. Geiss A. et al. and Zbontar, J et al. adapted the semi supervised learning approach for cloud classification [17][18]. Though lot of research is done there is lot of scope for the improvement. This research utilizes the combination of deep learning and machine learning for cloud classification from Sentinel-2 satellite imagery.

III. MATERIALS AND METHODS

Cloud classification is a common preprocessing required for deep learning. In this study, the proposed system is developed in three stages. First stage deals with building CloudS2 dataset. Second stage deals with implementation of Transfer learning approach as feature extractors and lastly third stage utilizes ensemble learning method as a classifier. The performance of the proposed system is assessed using evaluation metric. Block diagram of proposed method is depicted in Fig 1.

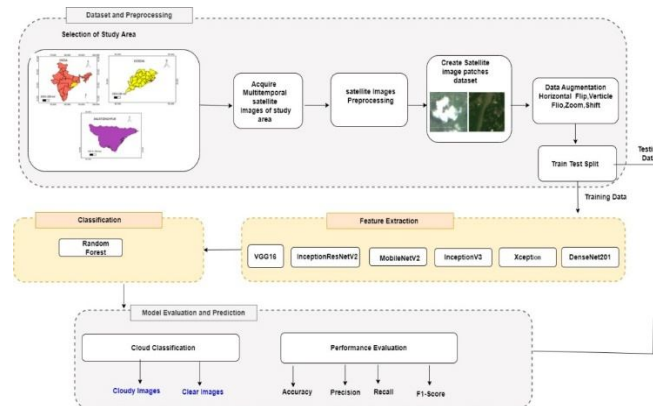


Fig 1. Block diagram of proposed system

A. Dataset

A dataset is essential to deep learning. A dataset entitled CloudS2 is proposed in this study. Below is a discussion of the steps involved in creating the dataset. Initially, the Jagatsinghpur district from Indian state of Odisha has been chosen as the study region. The coordinates of the location are 86°20'15.63"E and 20°11'51.3"N as longitude and latitude respectively. In the study area, July to September is considered as the rainy season. The majority of the time during the rainy season there exists a cloud cover. Sentinel-2 satellite images in multi temporal and multispectral domains are thus acquired for this research region. Images from satellites are enormous and intricate. Google Earth Engine (GEE), a cloud platform, has become a viable option in recent years. Users can obtain and utilize optical and synthetic aperture radar satellite pictures with GEE. Satellite images require preprocessing, such as geometric and radiometric adjustments. Preprocessing has already been done on the satellite data that is accessible through GEE. Thus, GEE is used to obtain multi-temporal Sentinel-2 satellite images. Sentinel-2 offers data in thirteen bands with different wavelengths and resolutions. A natural color composite of a satellite image is

created using the bands Band 4 (Red), Band 3 (Green), and Band 2 (Blue) with a resolution of 10 meters per pixel. Polygons are then drawn on satellite images and further exported as jpg and tiff files. While jpg photos lack geo referencing, tiff files do have it. Two classes—Cloudy and Clear—are taken into consideration for the dataset. Fully or partially cloudy images and cloud shadows are considered in the class of Cloudy images. The cloud free images are considered in the category of Clear images. These cloud free images include Built-up areas; water bodies, farming areas, and barren land. These cloud free images are considered in the class of Clear images. Fig 2 shows the sample images from CloudS2 dataset.



Fig 2. CloudS2 sample images

B. Data Preprocessing

Images vary in size. Therefore, it is essential to resize the image. All the images from dataset are resized to 128*128. Deep learning need huge amount of data for better performance. One method of producing new data from existing data is data augmentation. In deep learning, the term image data augmentation refers to a type of data augmentation wherein training data images are converted into new versions. In this work, augmentation is carried out using functions like shift, zoom, and horizontal and vertical flips on satellite image patches created in previous step. Following data augmentation, the collection's modest size is composed of 1262 photos. A total of 988 photos are utilized for training, while 247 images are used for testing.

C. Methodology

Deep learning has proved its capability in widespread applications of remote sensing domain. Deep learning algorithms are generally applied on satellite imagery acquired from various satellite sensors like Seninel-2, Landsat-8. Deep learning need huge amount of data to achieve the better performance. However, it is difficult to get such huge amount of data in real time applications. Transfer learning is an efficient solution to solve the aforementioned issue. Transfer learning is a way in which transfer of knowledge takes place from one task to another related task. In this study, transfer learning is used as a feature extractor and further these features are provided to ensemble learning based Random Forest algorithm. A total of 6 pre trained models a VGG16, MobileNetV2, InceptionV3[18], Xception[20], DenseNet201, InceptionResnetV2 are experimented as Feature extractor. Classification task is accomplished by using ensemble learning based the random forest algorithm. The extracted feature values from the best performing InceptionV3 model are sent random forest algorithm for classification. The RF algorithm was developed by L. Breiman in 2001 (Biau and Scornet 2016). Since then, it has been successfully adopted in various classification and regression analysis. Here in our work, the random forest takes input from the InceptionV3 feature extraction. Number of estimators for Random Forest are 50. The RF algorithm classifies the cloud images in one of the category of Cloudy or Clear images.

Let dataset CloudS2= (X_i, C_i) where X represents the number of images, C represents the class category $C = \{Cloudy, Clear\}$

Let $M = \{VGG16, MobileNetV2, DenseNet201, InceptionV3, InceptionResNetV2, Xception\}$ be set of pre trained deep learning models.

The detailed algorithm 1 is explained below.

Pseudo code for proposed model

1. **Input** : image patches (X, C) from dataset CloudS2
2. **Output**: Class label C_i where $C_i \in C$
3. BEGIN
4. Step 1: Divide dataset CloudS2 into DS_{Train} and DS_{Test} with split ratio of 80:20
5. Step 2: Resize input images as per requirement of pre trained model
6. Step 3: Perform Data augmentation and normalize

7. Step 3: Train pre trained deep learning models M_i as feature extractors
where $M_i \in M$
8. Step 4: input the extracted features in step 3 to Random Forest algorithm
9. Step 5: Compute accuracy of proposed model.
10. END

D. Performance evaluation metrics

The performance evaluation metrics are crucial to assess how effectively a deep learning model performs for a given task. In this work, the accuracy, Precision, Recall and f1-Score are used as a performance evaluation metrics of the Cloud classification task. As a measure of performance evaluation, accuracy shows how many right predictions the deep learning model has made overall relative to all predictions. Mathematical formula for accuracy is represented as shown in equation (4)

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (4)$$

Where FP: False positive, TN: True Negative,
FN: False Negative, TP: True positive values

Precision

Precision is the ratio of True positive to True positive and False positive.

$$Precision = \frac{TP}{TP + FP}$$

Recall

Recall is the ratio of True positive to True positive and False Negative.

$$Recall = \frac{TP}{TP + FN}$$

F1-Score

F1-score is defined as weighted harmonic mean of precision and Recall.

$$F1\ Score = 2 \times \frac{Precision * Recall}{Precision + Recall}$$

IV. RESULTS AND DISCUSSIONS

Experiments are conducted on CloudS2 dataset using transfer learning approach. All the experiments are conducted in Google Colab. The performance comparison based upon of accuracy of various approaches is depicted in Fig 3 and performance evaluation based on evaluation metrics like precision , recall is depicted in Fig

4.

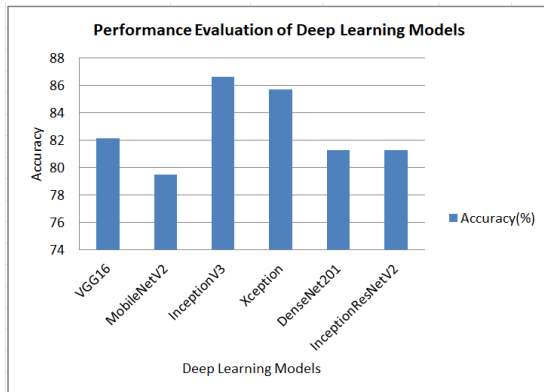


Fig 3. Performance comparison Accuracy of deep learning models on CCloudS2 dataset

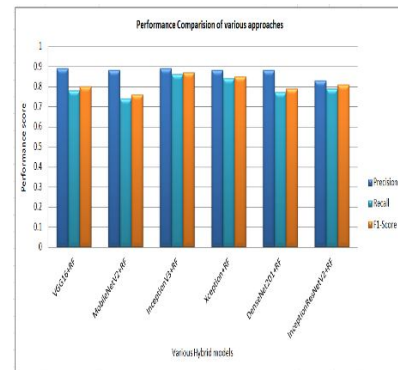


Fig 4. Performance comparison of deep learning models based Precision, Recall and F1-Score

The proposed model is implemented on CloudS2 dataset. The proposed model is a combination of pre trained deep learning model and Random forest. Deep learning pertained model is used as feature extractor and the extracted features are further sent as an input to the random forest algorithm. It is observed that MobileNetV2 model has shown the low performance whereas InceptionV3 model has shown highest performance. Xception model has shown good performance whereas DenseNet201 and InceptionResNetV2 and VGG16 have shown moderate performance in terms of accuracy. From the experimental results, it is evident that that time required to train the proposed model is less in comparison to others. The performance evaluation metrics like Precision, Recall and F1-score are also evaluated. Fig 4 represents the performance evaluation based on these parameters. It has been noted that the suggested approach still needs to function effectively in a variety of scenarios.

V. CONCLUSIONS

Cloud cover in optical satellite images poses several challenges in observation of features on earth surface. In this study, Integration of Deep learning and Machine learning is suggested to classify cloudy and clear images from Sentinel-2 optical satellite imagery. Deep learning need huge amount of data for better performance. However, it is challenging to acquire such data in real time. Therefore, Transfer learning concept is utilized for feature extraction and ensemble learning approach is utilized for cloud classification. The proposed model architecture is applied to Sentinel-2 CloudS2 dataset built from Sentinel-2 satellite imagery. The experimental results showed that the proposed model improved classification accuracy compared with other algorithms. The proposed model accomplished a classification accuracy rate of 86.6% for the testing dataset. It has shortened the running time. In future, we aim to test the proposed model on other study areas to check its generalization capability.

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