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RESEARCH ARTICLE

NDVI AND CUSTOMIZED CNN FOR LAND COVER SATELLITE IMAGE CLASSIFICATION

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Abstract

The efficient and the simplest deep learning algorithm of image classification is Convolutional Neural Network (CNN). In this paper we developed a customized CNN architecture for the classification of multi-spectral images from SAT-4 datasets. The sets Near-Infrared (NIR) band information as it can sense vegetation health. The domain knowledge of Normalized Difference Vegetation Index (NDVI) motivated us to utilize Red and NIR spectral bands together in the second level of experimentation for the classification.

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Introduction:-

Image classification is a one type of application in which we have a simple task for the human brain. While understanding the pixel relation, extracting the relevant features and classifying the images to different categories is difficult for the computers. Initially the classification of images was done by machine learning algorithms but now a days different algorithms required the help and assistance of domain experts for manually extract the features of the images. This classification tasks became simpler and fast by the development of deep learning which mimics the human brain by its neural network structure. In different sectors its application used like farming, bio-medical, remote sensing, vehicle navigation, robot navigation, surveillance etc.

Optimal feature extraction is the major task in image classification. Deep learning is capable of extracting the right features to the particular classification tasks used deep learning architecture in the context of image classification is Convolutions Neural Networks (CNN). It is a reticular formation that have a series of convolution, maxpooling and activation layers. They exploit the structure of images leading to sparse connections and helps parameter sharing between input and output neurons.In the classification accuracies most renowned CNN architectures like Alexnet, VGG net etc., used but these deep CNN architectures are involved with very high computations in terms of learning parameter and require high technical aid like GPU. The implementation of these architectures is well time consuming.

Main focused of this paper is on classifying land cover using satellite images. The main difference between the satellite images for land cover classification and normal images is the number of bands. The satellite image consists of 4 bands (Red, Green, Blue, and Near-Infrared). Normalized Difference Vegetation Index (NDVI) is the most common parameter used for land cover classification. Among the 4 bands which reside in a satellite image Red and Near-Infrared contains the relevant information to identify vegetation.[3],[4],[5]. The formula used for NDVI calculation is

$$\mathbf{NDVI} = \frac{\mathbf{NIR - RED}}{\mathrm{NIR + RED}}$$

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Where NIR represents Near-Infrared and RED represents Red band. NDVI makes use of two bands Near-Infrared and Red as the plants reflect Infrared and they absorb Red. NDVI values for different classes vary between -1 and 1.[6]

NDVI is capacious enough to be used as a measure for vegetation cover and yield. NDVI time series are used to derive the vegetation properties like length of plant growing season, greenness onset data, and a particular date on which maximum photosynthetic activity happens. A lofty NDVI value indicates hygienic vegetation and a shallow value indicates unhealthy vegetation.[7]

Related Works

The based work on SAT-4 and Sat-6 Landcover satellite Image classification was done by T TulasiSasidhar et al.,[1]. They made experiment on NAIP datasets. The work on the SAT-4 and SAT-6 DeepSat satellite imagery airborne datasets was done by SaikatBasu et al., [2]. They made the dataset publicly available and used Deep Belief Networks(DBN) for satellite image classification. Their semisupervised framework achieved 97.95% and 93.9% accuracies for Sat-4 and Sat-6 respectively. AnushreeRamanath et al.,[8]provides methods and analysis for land cover classification of remote sensing images. Satellite images form the input while mapping of every image to a distinct class is obtained as output.Zhice Fang et al.,[12] research on Landslides are regarded as one of the most common geological hazards in a wide range of geo-environment. The aim of this study is to assess landslide susceptibility by integrating convolutional neural network (CNN) with three conventional machine learning classifiers.

Dataset Description

In this section, we used the SAT-4 Airborne Data setand described in detail and a brief idea about them.

The entire SAT-4 dataset consists of a labelled set of 400,000 training samples and 100,000 test samples and has a size of ~1.36GB. sat-4-full.mat are MATLAB mat files that can be loaded into MATLAB using the standard ‘load’ function.

SAT-4-full.mat contains the following variables:

test_x	28x28x4x100000	uint8(containing 100000 test samples of 28x28 images each with 4 channels - R, G, B and NIR)
test_y	4x100000	Double(containing 4x1 vectors having labels for the 100000 test samples)
annotations	4x2	cell (containing the class label annotations for the 4 classes of SAT-4)

Fig 1:- An illustrative portrayal of DeepSat Land Cover Images.

The experiment is conducted on the NAIP(National Agriculture Imagery Program) extracted “SAT-4 airborne datasets” as shown in Fig 1 which are publicly available.[1] The average size of each satellite extracted image is 6000x7000 pixels and from these labeled uniform image patches, 28x28 disjoint sliding blocks were extracted inorder to avoid inter-class overlapping. While using this the author created two datasets[2].

Table I: -

DATASET	Trainable Parameters	
	NIR	Red & NIR
SAT-4	1,64,260	1,64,404

Trainable Parameters
A detailed description about these datasets we used are given in Table I. Dataset are comprised of 4-band (Red, Green, Blue and Near-Infrared(NIR)) 28x28 dimension images. SAT-4 data consists of four classes namely Trees, Grassland, Barren land and Other. The fourband data is converted into one band data consisting only NIR band and a two-band data which has only Red and NIR bands. The experiment is carried out on the newly prepared datasets.

Proposed Work
The architecture used in experimentation is given in Fig 2. The function of each layer is given as follows:

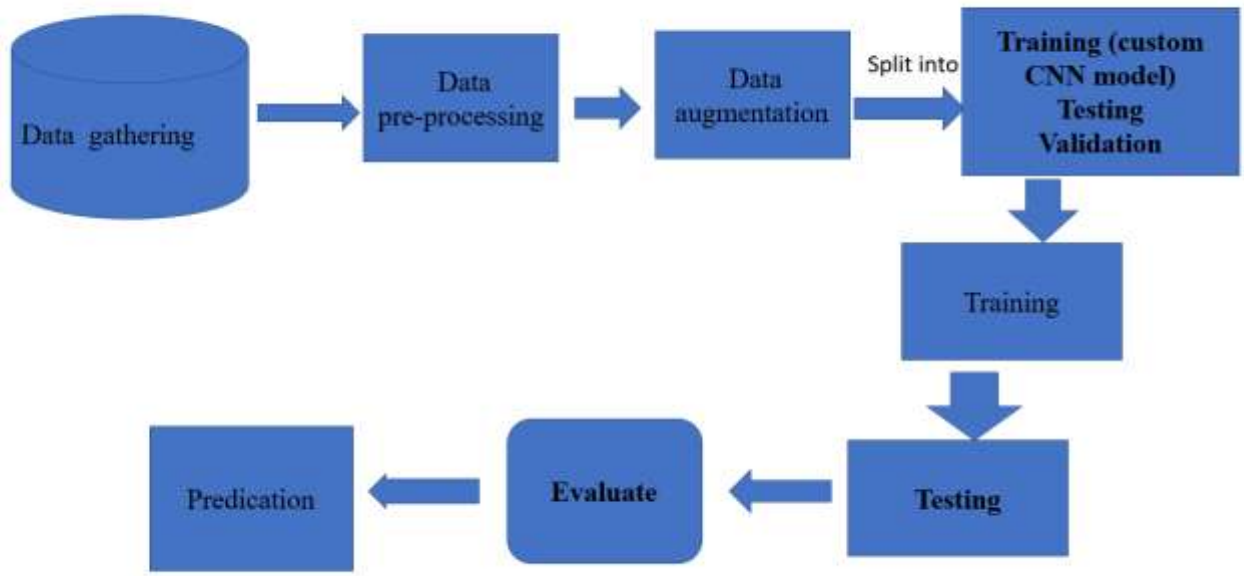

Fig 2:- System Data Flow Diagram.

1. **Data gathering**: - Process of gathering means data collection and measuring information from different sources. Data gathering is the basic step. There are largely three methods for data collection. First, method is to choose the right datasets for training models. Second method is data labeling which is necessary in all supervised learning applications. Last one can improve the quality of existing data.
2. **Data Preprocessing**: - It transforms on the raw data before it is fed to the algorithm. For instance, training a convolutional neural network on raw images will probably lead to bad classification performances.
3. **Data augmentation**: -It is a technique to artificially create new training data from existing training data. This means, variations of the training set image that are likely to be seen by the model. It is a one type of strategy to increase the diversity of data. It helps us to increase the size of the dataset and introduce variability in the dataset, without actually collecting new data.
4. **Training, Testing and Validation**: - it is a one method to measure the accuracy of the model. We split the data i.e. 80% training and 20% testing. Using the training set we train the data and test data used only access performance of model. While validation means when the process where a trained model is evaluated with a testing data set.
5. **Evaluate andPrediction**: - It's tested a model while evaluating different data and trained on for same. Training set is a subset of the dataset used to build predictive models. While prediction is a one technique in which output of the algorithm has been trained and applied to new data.
   While using the AlexNet we allow for multi-GPU training. his mean that a bigger model can be trained, but it also cuts down on the training time and customized the Convulation Netural Network and the total increse the size of trainable parameters as shown below:

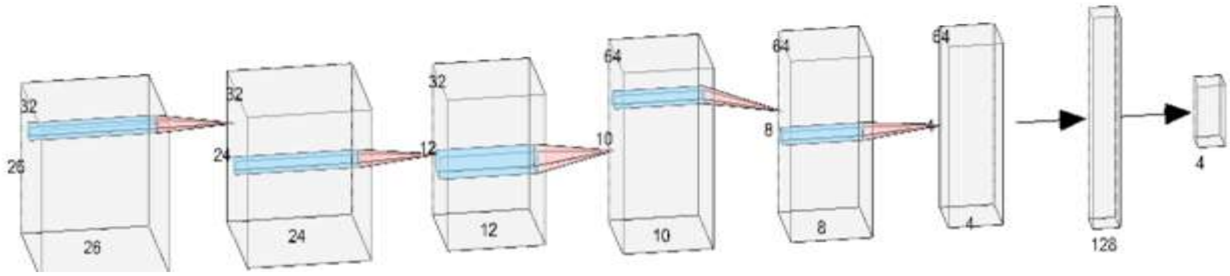

Fig 3:- Customized CNN Architechture.

'ReLU' is the activation function used all along the architecture and for the classification layer 'Softmax' is used. The total number of trainable parameters of this architecture are shown in Table II

Table II:- Trainable Parameters.

Total parameters	Trainable Parameters	Nontrainable Parameters
327,332	**326,500**	**832**

Conclusion and Future Work:-

This paper analyses the performance of a computationally inexpensive customized CNN architecture on SAT-4 airborne dataset for land cover classification The first testcase considered only NIR band as they can sense vegetation and both Red and NIR are taken together as second test case. The proposed model gave better performance when both bands are taken together

Due to the high variability inherent in satellite data, most of the current object classification approaches are not suitable for handling satellite datasets. The progress of satellite image analytics has also been inhibited by the lack of a single labeled high-resolution dataset with multiple class labels.

Fig 3:- Resultant Images of prediction.

By using sat-4 dataset after the prediction when input the image we got the output of

Trees

Prediction:

0.2% probability barren land,

0.0% probability grassland,

0.0% probability other

99.8% probability trees

It achieved a promising level of classification accuracies of above 99%. This work is limited to a dataset which contains 4-band multispectral images and the number of data classes are four. It can be extended to the 6-band as well as hyperspectral images which contains hundreds of band information and higher number of data classes.

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