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Real-time Satellite Image Classification Using Convolutional Neural Networks for Earth Observation and Video Feed Analysis

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Abstract

Satellite Image Classification is all about classifying satellite image datasets into their respective classes by assigning the correct class label. In supervised deep learning, we provide an efficient way of classifying earth observation imagery captured by satellites. By using Convolutional Neural Networks (CNN), we have achieved good accuracy as well as provided another way of testing the classifier by providing a video clip. This method has applications like live feeds from cameras or satellites, which can be processed frame by frame and tokenized, offering better accuracy rates. Furthermore, this approach enables real-time processing of satellite imagery for monitoring and analysis. Our model also demonstrates scalability, handling various satellite image datasets with diverse class numbers and dimensions. In this Satellite Image Classification paper, we have worked on different satellite image datasets, with varying class numbers and image dimensions. We have concluded results in this report, from which you will understand their details with respect to accuracy and performance.

Keywords:

Image Classification, Satellite Image, CNN, Tokenized.

1. Introduction

Since last couple of decades image processing has rapidly increase to shape it in new manor like its techniques and methods, due to this fact now we have a lot of High Resolution (HR) Images available to do image processing with large foundation details in these days. In this paper we worked on datasets like WHU-RS19 and AID dataset consisting almost 30 different classes as well as 10,000 images having 600x600 in resolution. As we look inside the dataset, we somehow found very much similar images like residential and industrial. Both classes are similar but different at some certain points like structural and spatial points which is also lead us to challenging side. In this paper we have worked on Bag of words (BoW) which is basically designed for text analysis by computing words frequency which is after/further adaptation it's being used for images to represent by its local features occurrences [1-10]. Those features are initially handcrafted by scientist but now this pre-processing workload is been responsibility of Convolutional Neural Network (CNN). But BoW didn't get results as much as we desire. So moved on to Convolutional Neural Networking (CNN). CNN is multi-structure architecture consisting 5 layers of convolution, fully connected layers, pooling. It works fully supervised manner.

So, by using CNN for satellite image classification paper it was difficult to train the entire dataset for pre-processing step like to extract features/feature learning step. For that we use transfer learning as pre-trained CNN for feature learning [24]. Pre-Trained CNN like AlexNet [25], CaffeNet, VGG-VD16. So, we applied this architecture of deep learning and got desired accuracy. We have explained the process in details as following to report.

Deep learning [12][13] is a category machine learning where it possesses several layers that are interrelated to one another and it's referred to as neural network. An image is presented in the following descriptions of Deep Learning in subsequent sections of this document [20]. It is a multi-layer architecture that are inter-dependent with one another which can learn features on its own and based on those features that Neural Network learned and after that Neural network will classify. For instance, another network with multiple layers including "pooling, dropout, sparsely connected layers, activation function like; Sigmoid, ReLU, Tanh, and softmax" so it will change its outputs according to its parameters (input values of node of layer, which may or may not an output values on node of layer) at runtime depending on above-stated parameters as we discussed now and giving priority of a layer to other layers that may rely on task or problem which we are working on. Deep Convolutional Neural Network (CNN) typically consisting of many layers with varied aspects of the task like at first or beginning layers capture features such as corners and edges etc. as presented in figure 1.

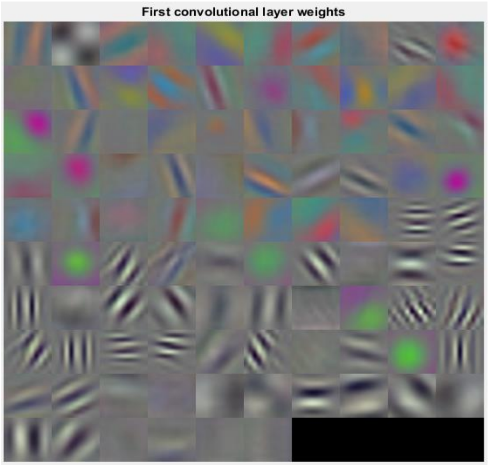


Figure 1 First Convolutional Layer Weights

1. Related work

Satellite images are basically the images those are taking by the artificially made satellites. Those images are whole or part of earth taking by artificial satellites and use for different purposes. As we know image contains information that we can use for different purposes. For example; Weather Forecasting, Military Defense Control (surveillance), Intelligence Agencies, Cartography, Thematic Heat Map, Traffic Control, Classification, Agriculture, Environmental Monitoring, Extracting Mineral Deposits, Providing a base map to engineers and planners for graphical reference and Disaster Mitigation Planning and Recovery.

Digital imagery can greatly enhance a GIS. Part of the raster data types; imagery is a powerful visual aid and serves as a source of derivative information such as plan metrics and classification schemes to derive such information as land use or vegetation. If your GIS covers a particularly large area, aerial imagery may not be a practical or economical choice. Satellite imagery is often the preferred choice of imagery for larger regions. More and more choices of satellite imagery are becoming available and the cost associated with its purchase is dropping.

Most of the satellite imagery can be bought directly from the respective agencies. There are also online websites that deal in satellite imagery sales. Plan graphics is a distributor of Space Imaging's IKONOS imagery. EOM Online sells a number of imageries like Landsat 5, IRS Imagery and Landsat 7. TerraServer is also a popular source of satellite imagery.

Classification is a process where various types, species or things to be identified or distinguishing from one another for further study or to research purposes. For instance, if we have various type of images and we need extract information based on "how many images have residential area?" so then in such case we need distinguish class named by "Residential Area" to research/extract information easily rather than searching from bulk of image dataset.

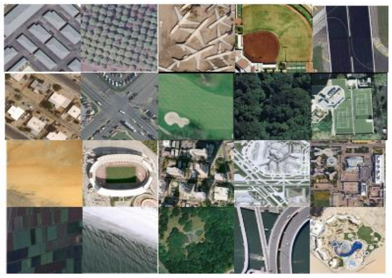
Another example; the researchers are of the view that on our planet, there are millions of various species of micro-organism, animals and plants existing on our planet at present. So in that scenario, in order to classify every various species for preserving its information and belonging, they divide into various classes named classification. In this paper, we operated on dataset RSDataset and AID Dataset. Both datasets were classified into number of various classes. As we informed you earlier, the HRS Dataset is categorized into 19 various classes as well as AID Dataset is categorized into 30 various classes on the basis of their images having earth observational data.

2. Methods and materials

3.1.Dataset Details

Dataset is the repository of data which can or cannot have discrete set of data files to similar with each other, having information about specific set of data like business transactions, day to day departmental store sales and purchases, Restaurant business information in the form of database. In this paper, we have utilized RSDataset. In this data set, it contains 19 various classes with data of various classes such as residential area, industrial area etc. Every class has 50-60 various but of the same class of images around. Every image is of 600x600 in size. Some of images as illustrated from various classes. UC Merced Land Use Dataset is that dataset which is being created (extracted) manually using the assistance of "USGS National Map Urban Area Imagery collection" from several but different cities.

(a)



(b)

Figure 2 Sample Image of dataset: (a) AID, and (b) UC

3.2.Feature Extraction

Features are the interesting portion of an image or we can also say that features are the relevant part of an image for that it will assist in computer tasks in computer vision. Task would be any/specific in computer vision. Feature would be usually relevant part of an image for which you need to utilize or extract information from. In this paper we got feature from satellite images on concerned dataset as we mentioned earlier for datasets. Features can be obtained by various ways. For feature extraction, there are various features' extractors in computer vision that assisted us in finding/obtaining relevant features from satellite images. We are providing you with some feature extractors list as below:

- SURF (Speeded up robust features)
- HOG (Histogram of oriented gradients)
- SIFT (Scale Invariant Feature Transform)

Those were some of the feature extractors in computer vision, you can find easily more details in Matlab Documentation. Now we will give you a short overview about Feature Detectors.

2.2.1. Feature Detector

As we discussed earlier about features and how the features can extract from dataset of satellite images with the help of feature extractors. Now, we will discuss feature detector. For instance, if we have to find anything or missing thing at home anywhere at certain place, we first locate its position where that concerned things of stuff to locate. Then we proceed with suitable counter measures to get/extract thing or information respectively. Similarly in computer vision first we detect features and then use feature extractor with the assistance of suitable method as well as tool to be discussed. Feature detection in computer vision is first level of processing which is widely done as first method/operation on images in computer vision.

2.2.2. Feature Vector

As we discussed feature, feature detection and feature extraction earlier. Feature vector will be discussed now. Feature vector is vector in which feature object is expressed in n-dimensional vector form. Which can be further processed. Several algorithms in machine learning need an objects' numerical representation, as this kind of representations makes them easily processable and analyzable statistically. When modeling images, the feature values may be equivalent to the pixels of an image, when modeling texts maybe term frequencies of occurrence. Feature vectors are synonymous with the vectors of explanatory variables employed in statistical processes like linear regression.

$$X = \begin{Bmatrix} x_0^1 \\ x_0^2 \\ x_0^3 \\ . \\ x_0^m \end{Bmatrix} \quad \text{Is the feature vector}$$

3.3. Bag of Features

In bag of feature is indeed addressing image category classification. This process is also addressing the bag of visual words. In image category classification, the technique labializes the category on an image in test portion of the procedure. Image category can have pictures about anything such as, human, trains, boats, dog and cats etc.

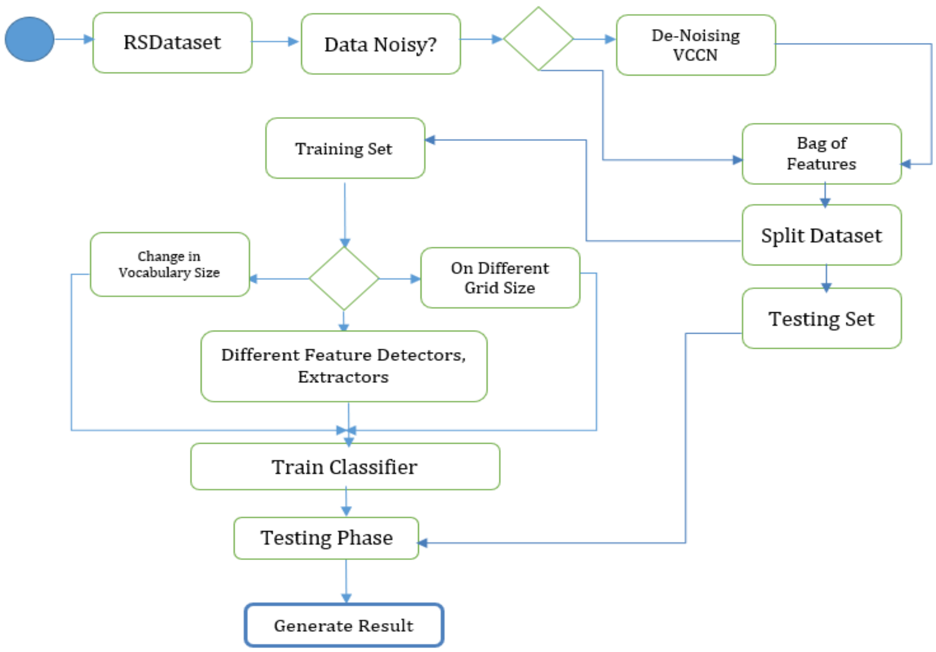


Figure 3 Bag of Features Diagram

In this process, initially we divide our dataset into training and test set. For that we can modify ourselves, then we can modify feature extractor as well as vocabulary size and grid size also. This process will create features and save it as bag that's why it is referred to as bag of features. Then from all those features, it will create histogram which states that each feature which machine learns and its frequency. After that process it will train the classifier for testing stage. For testing stage, one image will be given to classifier because testing image should be similar to unknown to machine or classifier otherwise there is no point of testing. It will display result as label of belonged class and its accuracy after test phase.

CNN Feature Learner

In the simplest form to explain convolutional neural network is the sliding window because function is applied to image matrix. As can be seen in figures. Convolutional Neural Network composed of set of input neurons with capability of learning of weights and bias values. Each connect layer transfers its weights to subsequent connect node.

We can presume this matrix on left side one as input values 0 for black pixel and 1 for white (actually 0-255 range for gray scale image) and in yellow 3x3 is a filter/kernel or feature detector. This would lead as convolved Features since it revealed in right 3x3 matrix obtained by piece-wise multiplication and then summation on all that will act as new pixel on convolved Feature matrix by sliding 3x3 kernel over the input image matrix. As it revealed above figure 4.

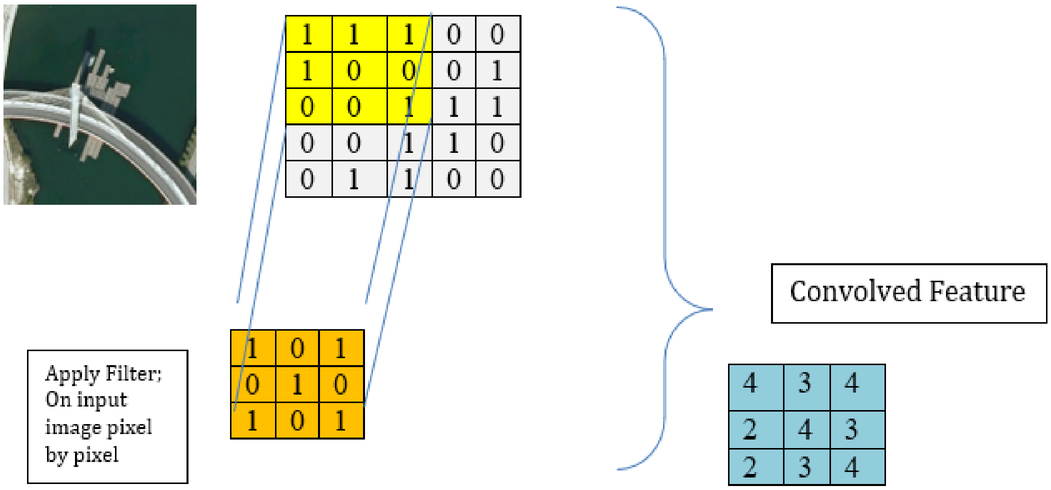


Figure 4 CNN Image Filter/Grid Size Diagram

3.4. Proposed methodology

In this method, we use Convolutional Neural Networking (CNN) and we got good results. First as you can see from the following flow diagram, we named it as Image Category Classification method for RSDataset that is why it starts with Dataset, but in reality, the method begins with Pre-Trained CNN "Alexnet". (High Level Experiments) we will discuss about it later that what is actually Pre-Trained CNN and High-Leve Experiments (Transfer Learning).

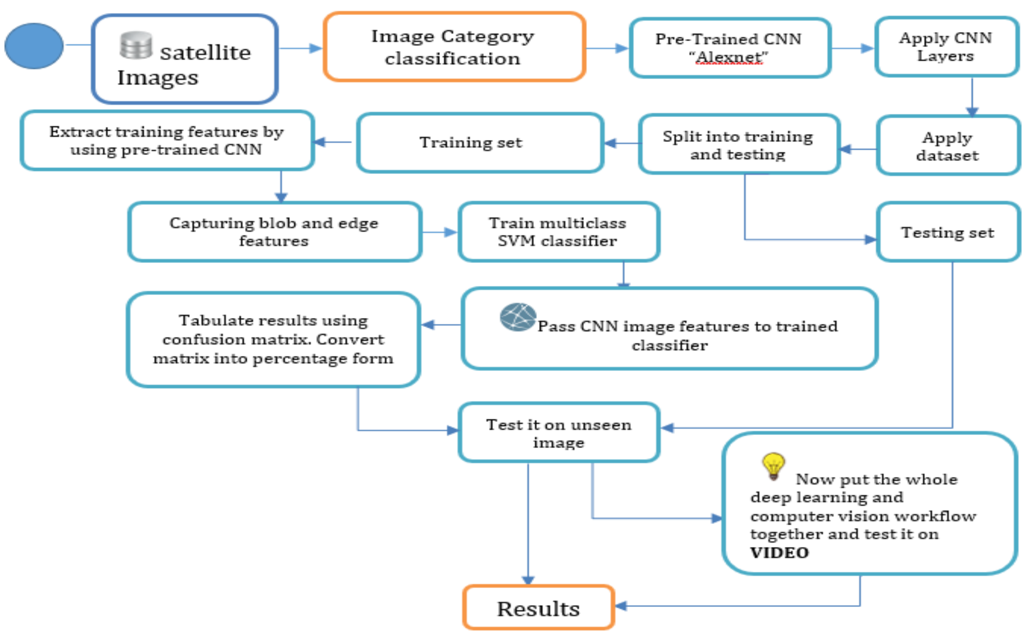


Figure 5 Proposed Methodology Diagram

First, it applies Pre-Trained CNN and then apply CNN layers, as we saw before the diagram (Hidden Layers). After the applying layers of CNN which involved pooling, convolution, dropout and activation function as well. Then we apply desired dataset which will split into training set as well as testing set. Extracting training features by using pre-trained which will help to capture blob and edge features from training set. That led us to the training multiclass SVM classifier. We will give an overview of Multiclass SVM Classifier later. Those CNN features then passed to the trained classifier those will be tabulated into results by constructing confusion matrix for percentage form. After this step we have testing phase. In this phase an image is provided to trained classifier which is completely unknown/new/unseen for multiclass classifier. The classifier will compare/process with an image and shows us result as inaccuracy and correct class name from which that test image belongs to. An additional thing we introduced for this method that what if we provide a video clip instead of an image or both. This paper will take/handle both testing ways and shows us result/prediction of belonged class.

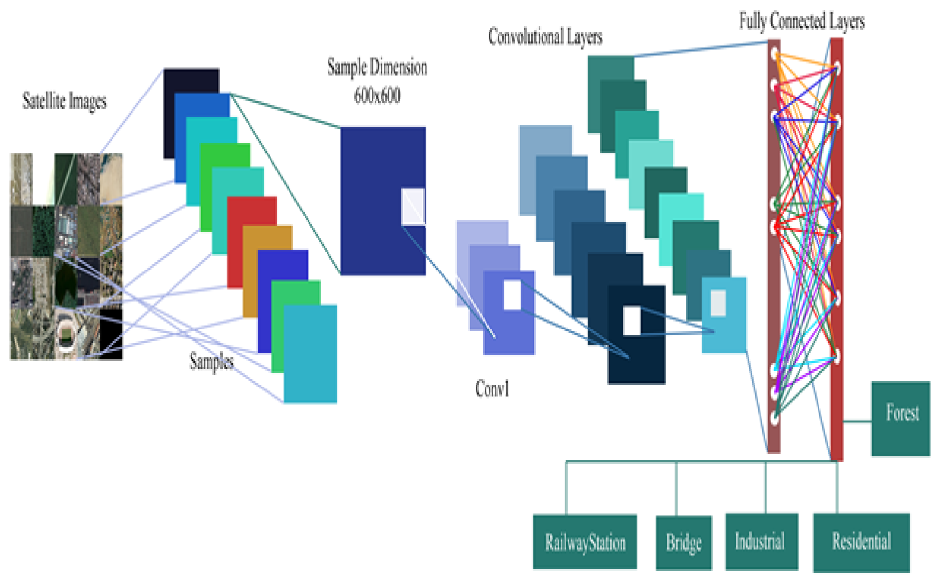


Figure 5 Feature Learning with Pre-trained Model Diagram

3. Implementation and results

In this section we will tell you what experimental study we have done. We divide it into 3 categories on the basis of experimental methods to compute different/distinct results. Details as following:

- **Low-Level**

At low level study, as we talked before about feature detector and extractors. We have worked/experiment with different kind of feature detectors to compute different results. For example; Sift, Surf, MSER, LBP, Mesh LBP, FAST, HOG etc.

- **Middle-Level**

At middle level study, we applied different methods with major customization like “Bag of visual words”. As talked before and explained before with flow diagram which explain that how it works. At achieved accuracy but that wasn’t enough of desired one.

- **High-Level**

At high level study, we applied transfer learning in Convolutional Neural Networks. Which is motivation to achieve accuracy that one we were looking for.

Table 1 RS DATA SET

NO	Dataset	De noised Dataset	Grid Size	Partition Ratio	Vocabulary Size	Random Images	Training Dataset Accuracy%	Testing Dataset Accuracy %	Feature Descriptor
1	RSDataset	Yes	[8 8]	0.3	500	No	0.94	0.61	SURF
2	RSDataset	Yes	[8 8]	0.3	500	Yes	0.95	0.70	SURF
3	RSDataset	Yes	[8 8]	0.8	Default	Yes	0.83	0.57	MSER
4	RSDataset	No	[8 8]	0.3	500	No	0.94	0.57	SURF
5	RSDataset	No	[8 8]	0.3	500	Yes	0.95	0.70	SURF
6	RSDataset	No	[16 16]	0.8	700	Yes	0.94	0.75	SURF
7	RSDataset	No	[16 16]	0.97	500	No	0.90	0.79	SURF
8	RSDataset	No	[32 32]	0.8	500	Yes	0.96	0.73	SURF
9	RSDataset	No	[32 32]	0.8	Default	No	0.91	0.55	MSER

4.1. Experiments for RSSCN7 Dataset:

Table 2 : RSCN7 DATA SET

No.	Dataset	De-noised Dataset	Grid Size	Partition Ratio	Vocabulary Size	Random Images	Training Dataset Accuracy %	Testing Dataset Accuracy %	Feature Descriptor
01	RSSCN 7	No	-	0.3	500	Yes	82.381	52.50	SURF
02	RSSCN 7	No	-	0.8	500	Yes	76.00	57.00	SURF
03	RSSCN 7	No	-	0.9	500	Yes	73.88	60.00	SURF

3.2. Experiments for AID (Ariel Imagery Dataset) Dataset:

Table 3 : AID DATA SET

No.	Dataset	De-noised Dataset	Grid Size	Partition Ratio	Vocabulary Size	Random Images	Training Dataset Accuracy %	Testing Dataset Accuracy %	Feature Descriptor
01	AID	No	-	0.3	500	Yes	89.00	42.00	SURF
02	AID	No	-	0.8	500	Yes	76.00	57.00	SURF
03	AID	No	-	0.6	500	Yes	69.672	33.03	MSER
04	AID	No	-	0.7	500	Yes	68.983	35.303	MSER
05	AID	No	-	0.8	600	Yes	68.674	35.152	SURF

There is array size limitation when you will go with vocabulary size of 700 for AID dataset with Customized Bag of feature method.

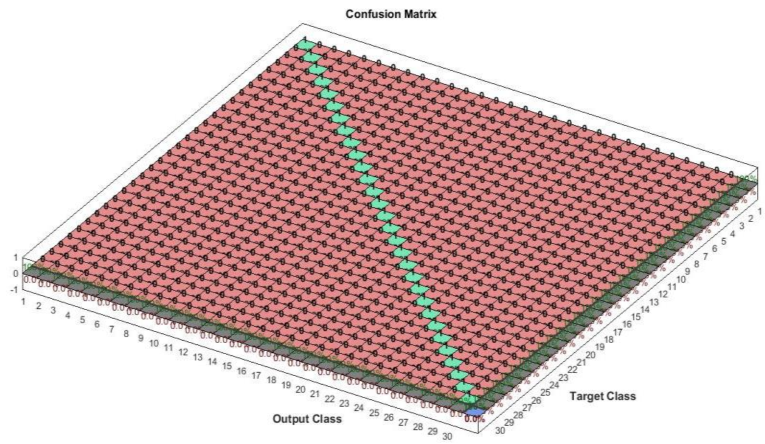


Figure 6: Confusion Matrix

These results were computed at low and middle level experiments with customization. Following results are having more customization as following:

Table 4 RS DATA SET with MSER+SURF

NO	Dataset	De-noised Dataset	Grid Size	Partition Ratio	Vocabulary Size	Random Images	Training Dataset Accuracy%	Testing Dataset Accuracy %	Feature Descriptor	SURF Vector Size	Block Size
10	RSDataset	No	-	0.8	Default	Yes	0.90	0.61	MSER	-	11
11	RSDataset	No	-	0.8	600	Yes	0.92	0.56	MSER	-	11
12	RSDataset	No	-	0.97	600	Yes	0.89	0.58	MSER	-	11
13	RSDataset	No	-	0.97	Default	Yes	0.87	0.74	MSER	-	11
14	RSDataset	No	-	0.97	400	Yes	0.86	0.42	MSER	-	11
15	RSDataset	No	[32 32]	0.97	Default	Yes	0.93	0.68	SIFT	-	11
16	RSDataset	No	-	0.97	Default	Yes	0.83	0.63	MSER+SURF	-	11
17	RSDataset	No	-	0.8	Default	Yes	0.86	0.45	MSER+SURF	128	11
18	RSDataset	No	-	0.8	Default	Yes	0.86	0.47	MSER+SURF	128	31
19	RSDataset	No	[32 32]	0.8	Default	Yes	0.94	0.74	SURF	128	31

In this section of results, we applied double feature detection technique instead of one as we done before to explore variations in results. So, we applied MSER+SURF and got following accuracy as shown in last table. After that we shifted to high level experiment as I said it was the motivation that were not attaining desired accuracy. So, we used Convolutional Neural Networking along transfer learning techniques/architecture. As I explained to you earlier along its working.

Table5: AID+RS+UC-Merced DATA SET and result

NO	Dataset	De-noised Dataset	Grid Size	Partition Ratio	Random Images	Testing Dataset Accuracy %	Method
1	AID	No	[8 8]	0.3	Yes	92%	Caffee-Alex
2	WHU-RS19	No	[8 8]	0.3	Yes	90%	Caffee-Alex
3	UC-Merced	No	[8 8]	0.3	Yes	89%	Caffee-Alex

4. Conclusion

In this Satellite Image Classification, we effectively utilized Convolutional Neural Networks (CNN) for classifying satellite imagery with good accuracy over a range of different datasets with diverse class counts and image resolutions. The method not only achieved good classification performance but also provided a novel method for evaluating the classifier with video clips, which makes it readily applicable to real-time processing for satellite imagery. This method accommodates live camera or satellite feeds processed frame by frame to provide fast and accurate analysis. Our approach is scalable and can be flexible with various datasets of satellite imagery, hence reflecting good potential in real-time analysis and monitoring of various applications. The findings of this research demonstrate the utility and the generality of CNN-based methods for classifying satellite images and provide prospects for extension and tuning in this field.

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