MOL2NET, International Conference Series on Multidisciplinary Sciences
USA-Europe Data Analysis Training Program Workshop

Land Cover Characterization of Satellite Images Utilizing Deep Learning Techniques

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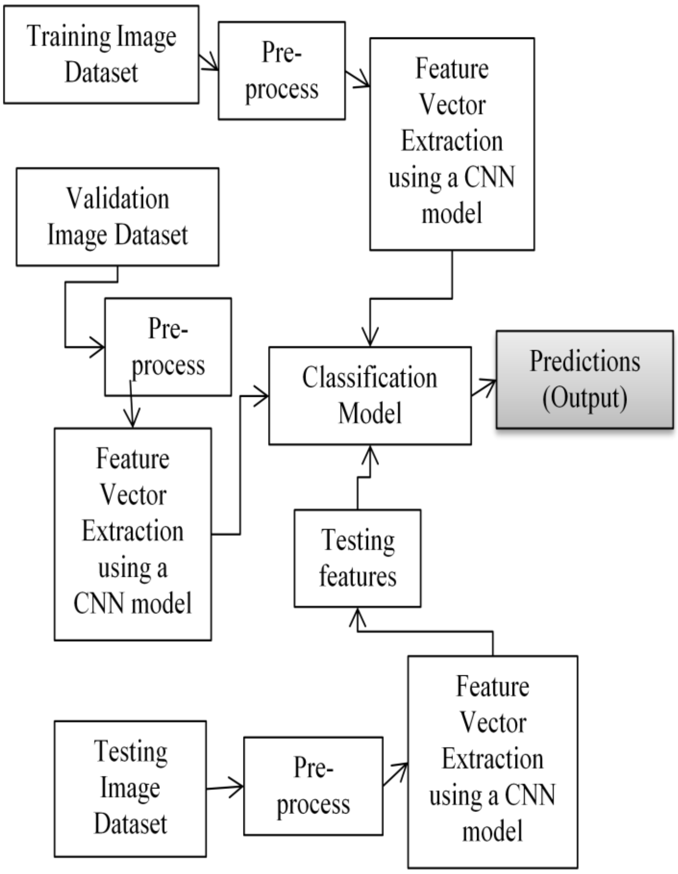
Graphical Abstract



Abstract.

In Earth Observation (EO) process the data is assembled about planet Earth through remote detecting. The area, where most information about our planet is gathered, is space. The data accumulated at the Earth's end is extremely huge, accordingly requires a great deal of manual work by people to recover group and foresee information gathered. To limit human exertion, neural networks were introduced. Counterfeit neural systems have accomplished the human level image grouping result. The issue of characterization of satellite images in the field of remote detection is commonly gained utilizing pixel-level, object-level, or scene-level. A Land spread characterization of satellite images using a Deep Learning strategy intends to accomplish uniform arrangement of land-structures. Utilizing a regulated learning procedure, the Convolutional Neural Network (CNN) model was created to classify satellite imageries. This for the most part centers on the scene-level arrangement of satellite images utilizing a Deep Learning strategy. At scene-level, the ability of CNNs to arrange or

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train_accuracy['Value'].value_counts().plot.bar()
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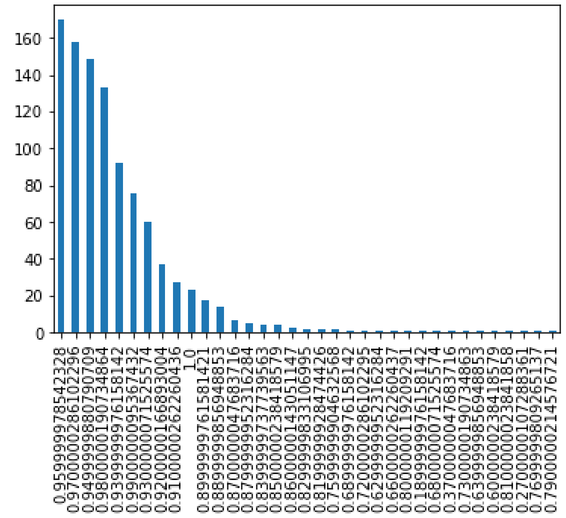


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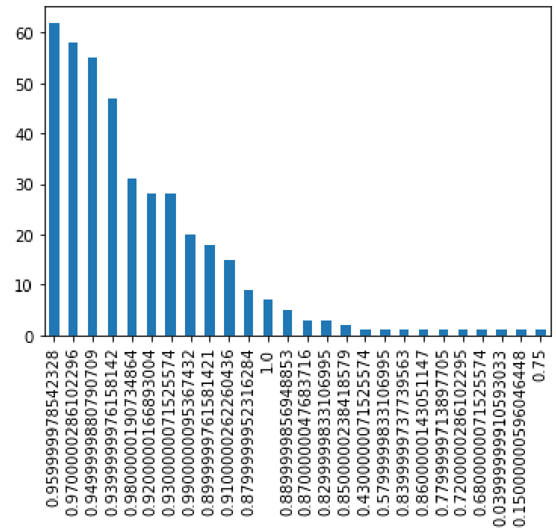

aggregate a tremendous number of remotely detected image information caught by different satellites has been examined utilizing various openly available datasets. Likewise, a trial dataset is utilized which has 0.5m resolution and was adjusted further according to the necessity. Utilizing scene level arrangement results are acquired by ordering respective images into numerous semantic groups. A survey and test are also performed to delineate and investigate how Deep Learning (DL) has been applied for remote image evaluation tasks for scene-level categorization.

This research work predominantly centers on a scene-level arrangement, of satellite images utilizing a Deep Learning method. Additionally, this report presents an exhaustive investigation of ongoing advancement on different datasets and techniques accessible for scene grouping. The different methodologies were discussed by distinguishing some exploration holes in Deep Learning for satellite data.

At scene-level, the capacity of CNNs to order or gathering a colossal number of remotely detected information caught by different satellites had been examined and investigated widely utilizing various openly available datasets. A detailed inspection and test were carried out to depict and examine how DL has been applied for remote detecting image examination tasks for the scene-level grouping. In the field of Remote Sensing, this examination covers the vast majority of the application and innovation in going from pre-training to the mapping of satellite images.

Introduction

The investigation of Deep Learning methods in satellite image classification has surprising consideration as it expects an essential activity to a wide extent of uses. The spectral and spatial detail of our ecology we acquire from remote detecting and satellite imagery holds immense measures of information that is standing by to have the best knowledge drawn out of them. Consequently, the inspiration for the research was to direct a comprehensive study of remote detecting field having associations with deep learning which incorporates scene categorization.

Research objectives are as follows:

1. Study various publicly available datasets and build an experimental dataset from a large satellite imagery.
2. Study and implement pre-trained model for satellite image categorization.
3. To develope a CNN model for satellite image categorization and make accurate predictions.

There has been a vast development in Deep learning in many fields but, still there exists an absence of profound survey for the datasets and strategies accessible for scene characterization from the satellite data. In this manner, this endeavored work was centered on edifying the idea and progress of Deep Learning all together at the scene level of airborne/satellite images.

Materials and Methods

An existing, 3 band (RGB) color datasets namely PatternNet, and one high-resolution modified experimental dataset were used to achieve the objectives and perform experimental analysis for satellite image categorization.

The Python programming language is utilized for test examination and to accomplish the targets in light of the fact that not just it is an open-source elevated level programming language yet it likewise approaches extraordinary libraries and structures of Deep Learning and AI which are the prerequisites of this task. Anaconda Navigator has an enormous number of libraries/bundles and applications helpful for managing Python programming language and is quicker than Python IDLE. Likewise, by virtualization, it gives numerous conditions that are exceptionally useful in taking care of enormous information calculation. Yet, to lessen program execution time and different complexities identified with framework memory and different bundles establishment, Google Colab was also used. For the handling of satellite images ERDAS IMAGINE software was used.

An experimental analysis of satellite image classification using Deep Learning approach was performed by firstly creating a virtual environment followed by installation of all the required libraries and packages. Then, a folder containing sub-folders was created and labeled as per the images in it. Again, the data was split into three categories, i.e.; test, train, validate. Further training was performed on image classifier using feature vectors computed by a pre-trained model which is trained on ImageNet. By running the training commands a model file and a label file was developed. Using the developed model file and label files the required results were obtained.

A pre-trained model of MobileNet 2 is used. The essential structure of MobileNetV2 is basically a Bottleneck Depth-separable Convolution with residuals present.

Initially, a virtual domain was created, and afterward different modules, libraries/packages were introduced, those were OS, GLOB, ARGPARSE, TENSORFLOW, KERAS PANDAS, SUBPROCESS, NUMPY, PIL, MATPLOTLIB, IMAGE, __FUTURE__ and so on.

The image classifier is prepared by utilizing the element vectors figured by Inception V3 prepared on ImageNet, which depends on a TensorFlow module which computes image feature vectors hub. Expecting InceptionV3 for each image 2048-dimensional vector as info is gotten as the top layer. Over this portrayal, a Softmax Layer is prepared. Let N be the number of labels in Softmax Layer. At that point, for biases and weights, it corresponds to learning N+2048×N model parameters.

For image classification purpose where training is involved, the sub-folder names are important and notable, since they portray the names applied to each image; in any case, the filenames themselves don't have any kind of effect. In like way, an imprint or name for any image is taken from the name of the sub-folder it is placed in. By running the training command a model file was developed. The developed model file is laden in a TensorFlow program code.

The visuals of modified high-resolution experimental dataset are shown in result section.

The graph plots of validation accuracy and training accuracy of developed model are also shown in the next section.

Results and Discussion

The validation accuracy is the precision (percentage of correctly-labeled images) on a randomly selected group of images from an alternate set. The training accuracy shows the percentage of the images used in the current training batch that were marked and labeled with the right class.

The validation accuracy and the training accuracy of the developed model are shown by graph plots which are approx. 96% for training accuracy and 95% for validation accuracy.

```
#plt.plot(train_accuracy['Value'], label='train')
plt.plot(validation_accuracy['Value'], label='validation')
plt.ylim((0.80, 1.005))
plt.legend();
```

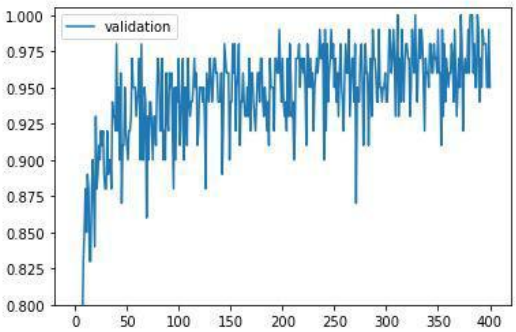

Figure 1. Validation accuraccy plot

```
plt.plot(train_accuracy['Value'], label='train')
#plt.plot(validation_accuracy['Value'], label='validation')
plt.ylim((0.80, 1.005))
plt.legend();
```

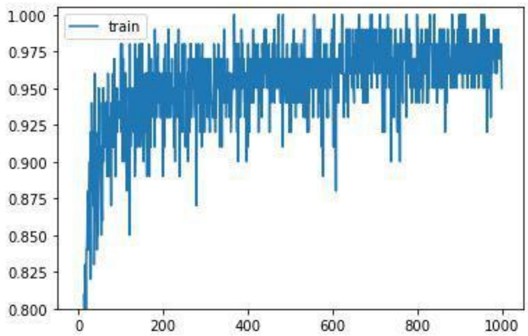

Figure 2. Training accuracy plot

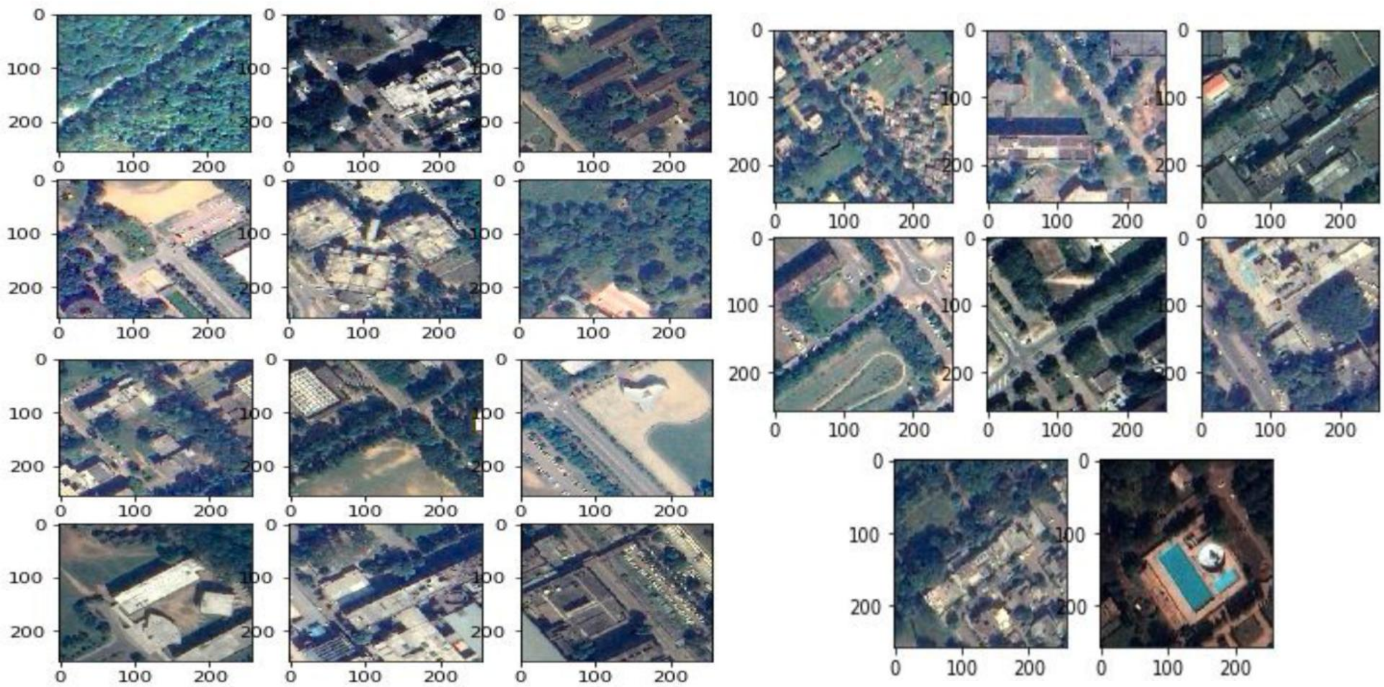

Figure 3. Visualised satellite images from the modified experimental dataset (A part of Chandigarh, India)

Visualized images from modified experimental dataset and their respective outputs predicted by the developed pre-trained CNN model are as shown below:

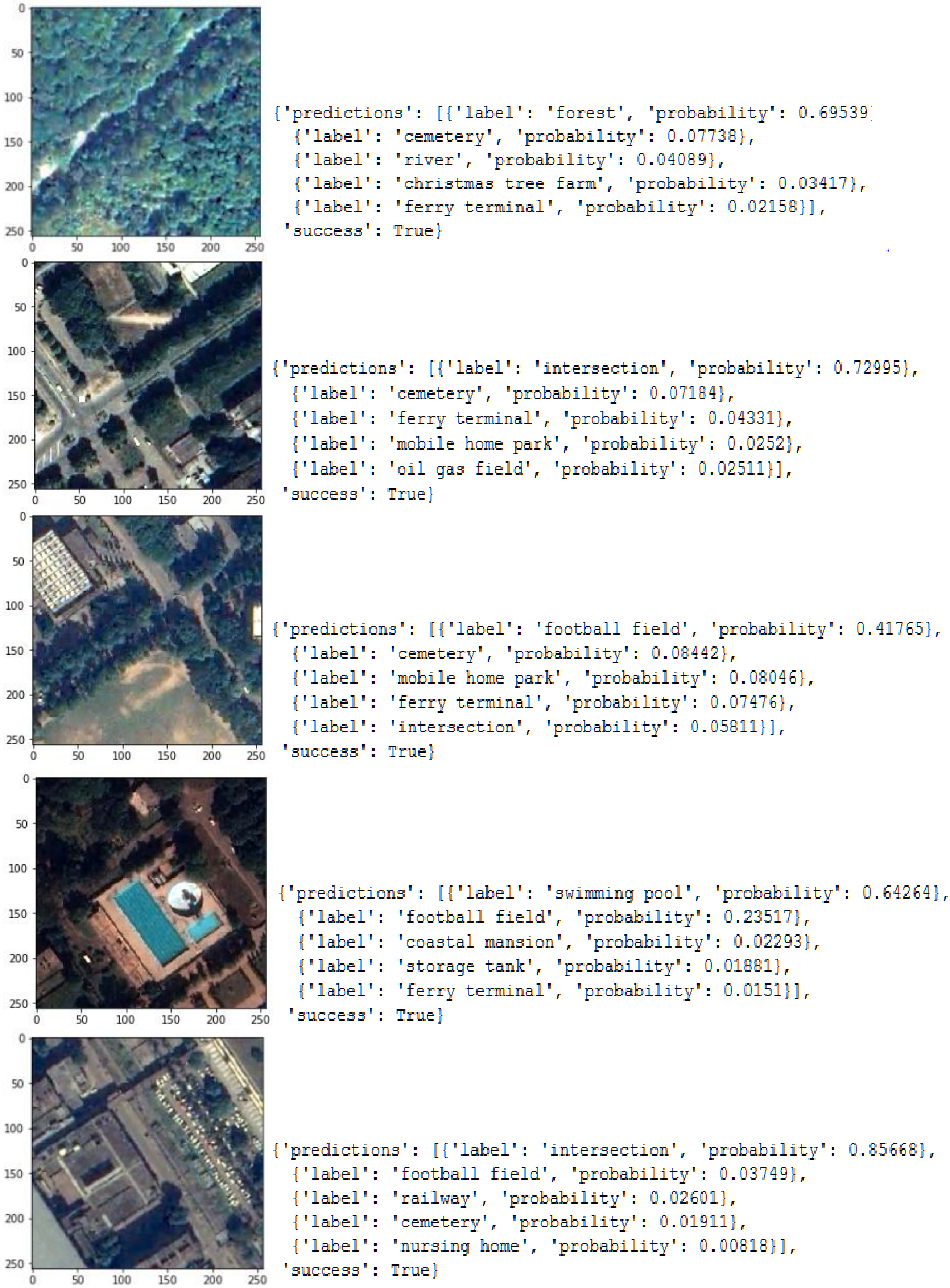

Figure 4. Predicted outputs from the modified experimental dataset

Conclusions

The outcome of the research work for satellite/aerial image classification problem using neural network with optimization techniques is summarized in this section. This paper addresses the implementation of robust image classifier for satellite/aerial images.

At the scene-level, the ability of CNNs for satellite remote sensing imagery classification has been comprehensively investigated on various transparently accessible datasets. In such manner, a convolutional neural framework was viewed as an outstandingly solid and precise technique for satellite and aerial imagery classification.

On the hypothetical side, utilization of MobileNetV2 permits a memory-proficient inference and simply relies on utilizing standard tasks present in neural systems. Moreover, on the contrary side, the convolutional block of MobileNetV2 has a remarkable property that approves detaching any system expressiveness encoded by bottleneck inputs. Exploring this hypothetical side is the important direction for further research.

Here only three bands (RGB) were used but it should be extended to use four band(R, G, B, NIR) satellite images as future work for image classification.

The limitation of using scene level approach for image classification is that there is loss of information because of the existence of class within a scene without identifying its inch-perfect location which can be overcome by translating it to pixel level one by convincing CNN during training to add further weights on the pixels. Thus, this should be the focus of future work.

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