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# Deep Learning for Satellite Picture Classification

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**ABSTRACT**

Applications such as emergency management, law enforcement, and environmental monitoring all rely heavily on satellite images. For these purposes, human facilitation and object identification are required. The enormous number of potential search areas and the scarcity of available analysts make automation a necessity. Yet, standard approaches to item identification and categorization are limited in their ability to provide a solution due to their emphasis on correctness and precision. Some progress has been made on automating these processes using the supervised neural class of machine learning algorithms. Evidence suggests that neural networks based on convolution may improve image recognition as well as comprehension. Here, we employ them to determine how to distinguish man-made features from natural ones in multispectral, high-resolution satellite images. Using the IARPA Functional World Map (fMoW) dataset, we offer a deep learning method for categorizing features and infrastructure into 63 categories. Visual features and satellite data are integrated using neural networks based on convolution and other artificial neural that form the backbone of the system. Built in Python with the help of the deep learning frameworks Keras and TensorFlow, it is deployed on a Linux server equipped with a Geforce Titan X graphics card. In the fMoWTopCoder competition, the system is now ranked second. Its F1 score is 0.797, and its total accuracy is 83%, with 15 out the of 16 classes properly classified (95% or higher).
**Keywords:** Convolution neural networks, Deep Learning, Python, Keras, TensorFlow, Satellite Imagery, Objects, Areas, Datasets, Linux Server.

## 1.INTRODUCTION

Machine learning models belonging to the deep learning family abstract information by layering representations of the data. Its amazing performance in object identification and classification may be attributed to the fact that it combines high-powered graphics processing elements with massive neural network models, known as deep neural networks (CNNs) (GPUs). The Image Net Large-Scale Visual Recognition Competition's goal is to recognize and categorize objects in photographs, and since 2012, CNN-based methods have won the competition. Several of the largest online corporations have already released CNN-based goods and services as a direct result of this breakthrough in visual interpretation. A CNN has many processing stages. Several convolution filters are applied to the picture at various stages. Further layers give advanced feature detectors that, at first glance, seem like the color blob and Bag - of - visual filters in Fig. The CNN provides a set of posterior probability, one for each class, by integrating the sensor outputs in the season finale of fully linked "dense" layers. CNNs can be taught without the need for the inventor of the algorithm to manually build feature detectors, unlike previous approaches like SIFT and HOG. During training, the network learns for itself which features are most important, and how to prioritize them. First developed for reading handwritten ZIP codes, the earliest successful CNNs had less than 10 layers. AlexNet consists of eight layers, whereas LeNet only contains five. There has been an ongoing trend toward greater complexity ever since. In 2015, Google introduced Inception, a 22-layer model, followed by the 16-layer VGG. Newer versions of Inception have several more layers. The ResNet network consists of 152 layers, whereas the DenseNet network has 161. These huge CNNs would not be possible without the processing power offered by modern GPUs. Accelerating GPUs and free deep learning libraries like Tensor and Keras have sped up development in the field.

## 2.LITERATURE REVIEW

### Scale-invariant keypoints reveal distinctive picture characteristics

This study proposes an approach for reliably matching between various viewpoints of an item or scene by extracting distinguishing invariant elements from photographs. The characteristics are proven to be robust in matching scenarios with varying degrees of affine distortion, 3D perspective shift, noise introduction, and illumination changes, and they also display invariance to image scale and rotation. A single feature may be properly matched against a large library high probability of features from several images, based on the features' distinctness. A strategy for applying these characteristics to object recognition is also detailed in this work. The object's identification is confirmed via the use of a lowest solution for constant posture parameters and a fast nearest-neighbor technique for comparing features to a library of features of known objects. This method of object identification can recognize objects with high accuracy despite background noise and partial obfuscation, and it can do it in near-real-time.

### For human detection, directed gradient histograms

Using linear support vector machines for identifying people, we investigate the issue of feature sets for accurate visual object recognition. In this work, we compare and contrast the government edge- and diffusion descriptor with grids of HOG descriptors, and conduct an experiment to demonstrate the superiority of the latter over the former in the context of human identification. We analyze the impact of each computing step on performance and find that relative high contrast normalization in overlapping descriptors blocks, fine-scale gradient, and fine orientations binning are crucial. Despite the fact that the new technique achieves almost flawless distinction on the initial MIT foot collection, we provide a more difficult collection comprising with over 1800 tagged person images with a wide variety of lineup changes and backdrops.

**Deep convolutional neural networks for ImageNet classification**

To achieve this goal, we divided the 1.3 million high-resolution photos that made up the Vessel cells ImageNet training set in 1000 classes using a massive, deep convolutional neural network. Our top-1 or top-5 margins of error on the testing data were 39% and 18%, respectively, lower than the prior best-practice values. There are five convolutional layers in the 500,000-neuron neural network, a few of which are followed by at the very most layers, two globally linked layers, and a final converters softmax. We developed a convolutional network that was trained quickly using non-saturating neurons and a robust graphic processing unit (GPU) implementation. We successfully applied an unique regularization strategy to drastically reduce overfitting inside the globally connected layers.

## 3.METHODOLOGY

The fMoW dataset's goods and infrastructure were classified by our deep learning system.A bounding box that identifies an object's position is inputted into the system along with a satellite picture and other information. It separates the data into 63 categories, one of which is "false detection."The system comprises of a group of neural networks (NNs), image processing algorithms, and CNNs.add the picture information and CNN image characteristics together. The ensemble generates prediction probabilities for the 63 classes by averaging the NN outputs without regard to their relative importance.The categorization is made based on the highest possible likelihood.

Python was used to implement the system together with the deep learning libraries Keras and TensorFlow. We ran the tests and training exercises on CentOS Linux-based servers equipped with Geforce Titan X GPUs. After extensively discussing each part of the system, we will outline the methods we used to train it.

A satellite picture and a bounding box defining the item or facility to be identified are used as inputs in the training and operation phases of the machine learning system. Before any cutting or scaling occurs, the image's bounding box is appropriately scaled up during the preparation process. At this point, we provide CNN its first set of context pixels to process. Instead, it maintains the aspect ratio by stretching the smaller dimensions to fit the space of the bigger one, thereby squaring the bounding box. (After using this squaring technique, we discovered that some CNNs performed much better than others.) The picture is then resized and cropped to fit the bounding box so that the CNNs can interpret it.

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## 4.IMPLEMENTATION

### CNN ALGORITHM

Convolution Neural Network for deep learning algorithms. It used for image recognition. Layers used in it is convolution , polling and fully connected layers.

CNNs The reduced images are then submitted to the CNNs for further processing. An ensemble is the basic unit of our deep learning system. used rather than a single CNN. By merging the outputs, a considerable improvement may be achieved since each CNN classifies the inputs into distinct classes differently. Inception-v3, ResNet-152, DenseNet-161, and Xception make up the CNNs. We first employed shallower CNNs, including ResNet-50 and VGG, but later discovered that the deeper CNNs gave superior results.

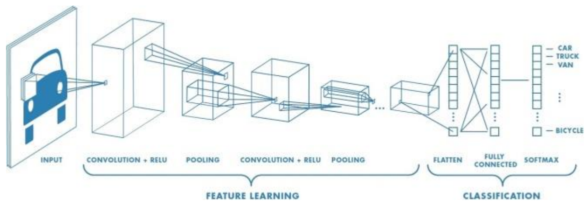


Fig 1: Example of CNN layers.


Fig 2: Adjusting the image.

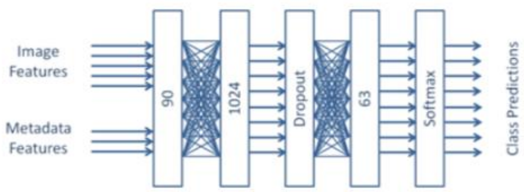


Fig 3: Class Prediction

## 5. MODULES

- Upload satellite image dataset
- Extract features from the dataset
- Train CNN Algorithm using this module CNN training
- Accuracy graph using the module
- Classification of images

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## 6.RESULT AND DISCUSSION

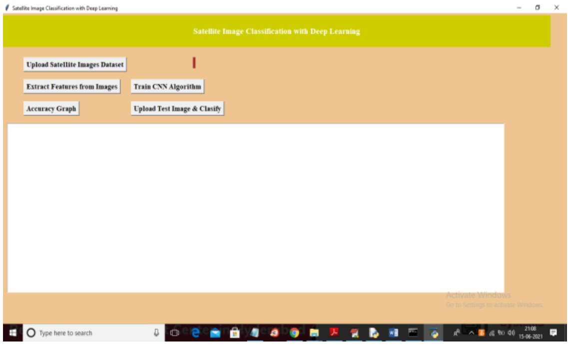


Fig 4: Home Page

- This is interface of our project.

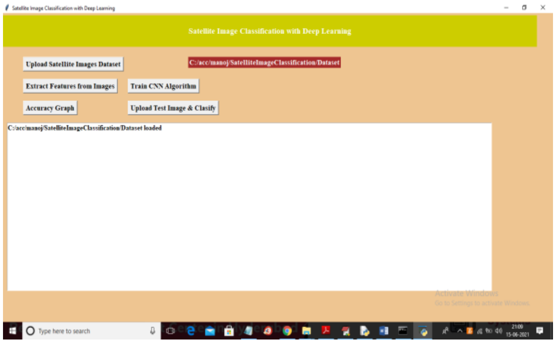


Fig 5: Uploading the Satellite Images Dataset

- Here we are uploading dataset and train the algorithm.

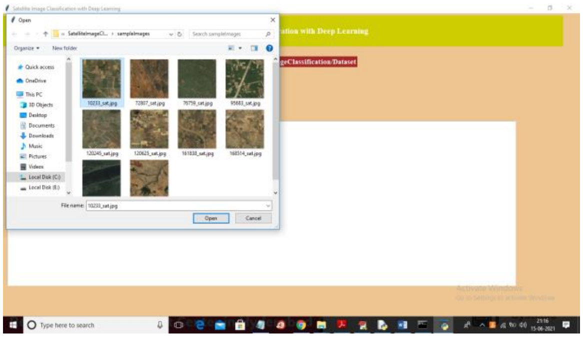

Fig 6: Testing Images

- Here we giving test image.

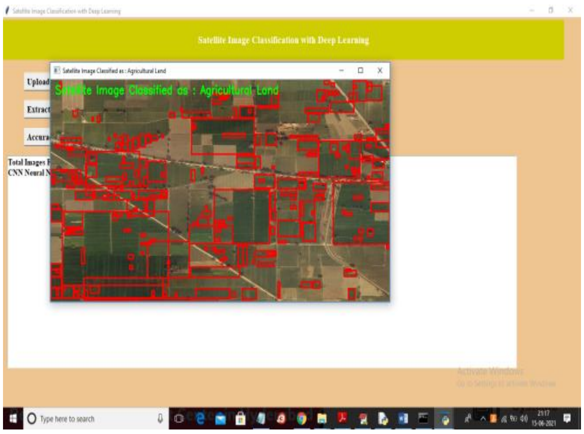


Fig 7: Classification of Image

- Here we are classify the image.

## 7.CONCLUSION

We have shown that a deep learning system can successfully identify and label structures in high-resolution multi-spectral satellite data. The system is made up of a group of CNNs that take satellite data and forecast outcomes using additional neural networks for post-processing. The system obtains an efficiency of 0.83 as well as a F1 measure of 0.797 over a million photos in 63 categories (such as the false alarm class) of the Independent assessment fMoW dataset. It improves over the John Hopkins APL model by 4.3% in the fMoWTopCoder competition, where it successfully classifies 15 classes with a success rate of 95% or above. Our method allows us to scan vast amounts of satellite footage for potentially important landmarks using a detector. This might be useful in resolving some of the initial concerns expressed about this investigation. By keeping a watch on a database of satellite photos, it might help rescue workers plot the impact of storms and mudslides, law enforcement uncover illegal mining operations, and investors monitor farm expansion and oil well drilling.

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