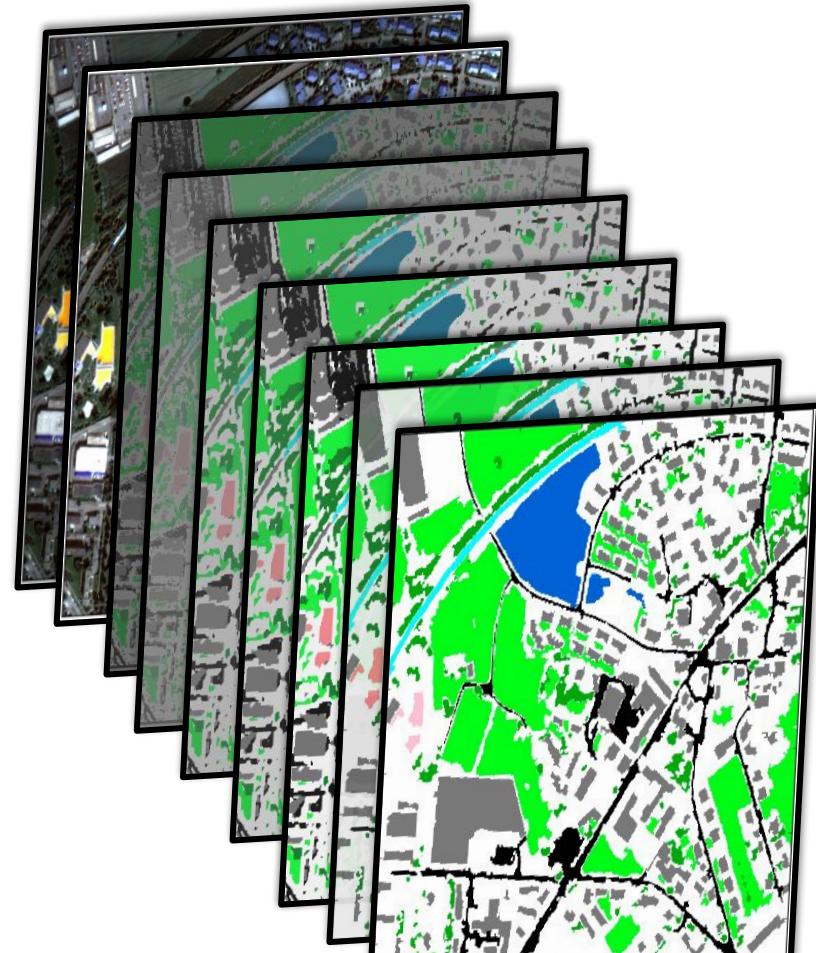




The Eye in the Sky

7th Inter IIT Tech-Meet, 2018



Outline

- Beginning & Need
- Classification Approach
- Model Overview
- Methodology & Implementation
- Results
- Output optimization-how and where

Beginning

- Before **1972**, satellites were mainly used for **military** missions.
- On July 23, 1972, Landsat1 (initially named **ERTS**), was the first satellite to study and monitor the Earth's surface.
- **Imagery** was commercialized in **1984**
- The **Land Remote Sensing Policy Act of 1992** embraced the value of remote sensing technology, promoted research and public sector applications, and allowed commercial companies to launch satellites and sell imagery.
- Thereafter, Earth observation satellites specifically designed for long-term **global observations** of the land surface, oceans, biosphere, and atmosphere.

Over **4,900** satellites orbit Earth today, and the space landscape is rapidly changing. Commonly-used satellites are both from commercial to government-sponsored and include WorldView, QuickBird, IKONOS, Landsat, MODIS, AVHRR, TRMM, and many others sponsored by many different companies and nations.

Need

Satellite images hold a large amount of data and plays a major role in **extract** and **interpretation** of valuable information from massive satellite images. Satellite image classification is required for:

- Spatial data mining
- Extract information for an application
- Thematic map creation
- Visual and digital satellite image interpretation
- Field surveys
- Effective decision making
- Disaster management

India needs to be digitally mapped. Most of the existing services of GPS are provided based on the data extracted and inserted manually on to the databases of online map resources like Google Earth and Wikimapia. The advancement in Image processing is necessary to terminate the **heavy expense of imagery analytics** and interpretation often performed by **human** imagery analysts.

Image Classification

Pixel-Based

Supervised

● Neural Network

● Decision tree



Unsupervised

● SVM

● K-Means

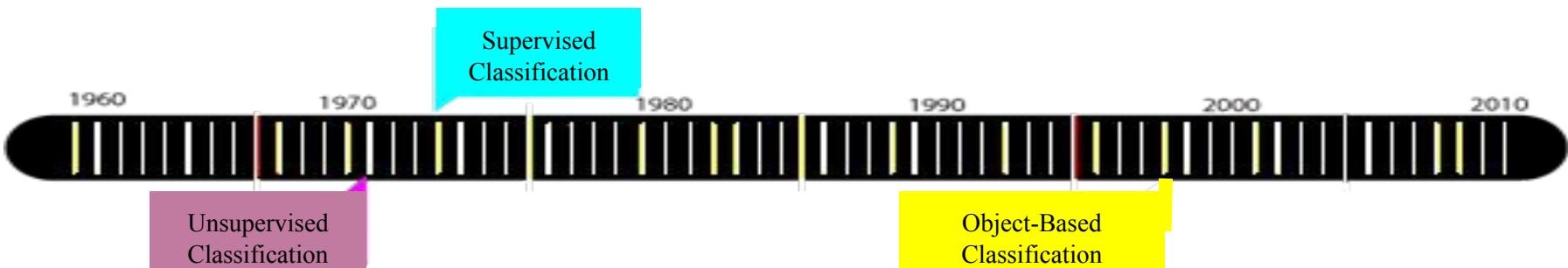


Object Based



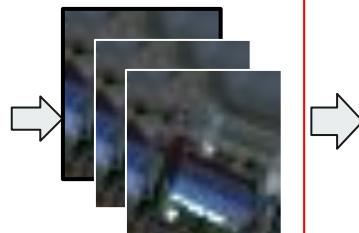
Comparing various methods

Supervised Classification	Unsupervised Classification	Object-Based Classification
<ul style="list-style-type: none">Divides into finer subcategories, such as species level classesLess human supervision than OBIATrained using a relatively small number of samples	<ul style="list-style-type: none">High human supervision requiredLabels need to be assigned manually	<ul style="list-style-type: none">Lack of direct transferabilityOBIA settings are not directly portable to other imagesTraining requires ample amount of samples

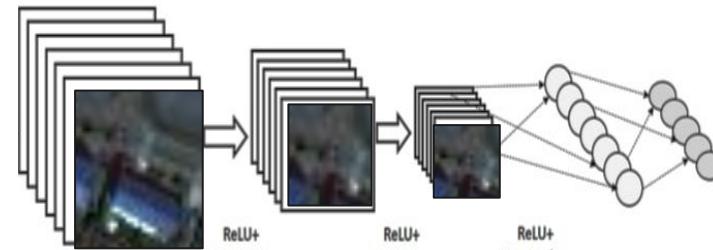


Overview

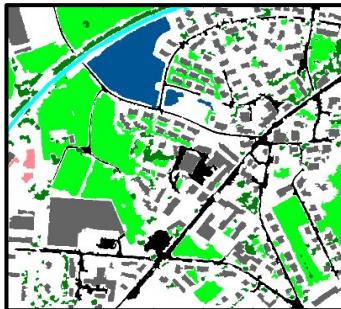
Input Processing



Model



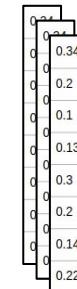
Smoothening



Output Processing



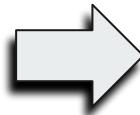
0	0	0	1	3	5	2	3
5	7	8	3	2	5	2	2
5	6	8	4	3	2	4	6
6	8	8	9	4	7	3	6
8	7	4	7	4	8	3	8
3	6	3	6	2	6	5	2
5	7	9	0	0	1	3	6
3	5	7	8	9	9	5	2



Input Processing



1295 x 1364 x 4

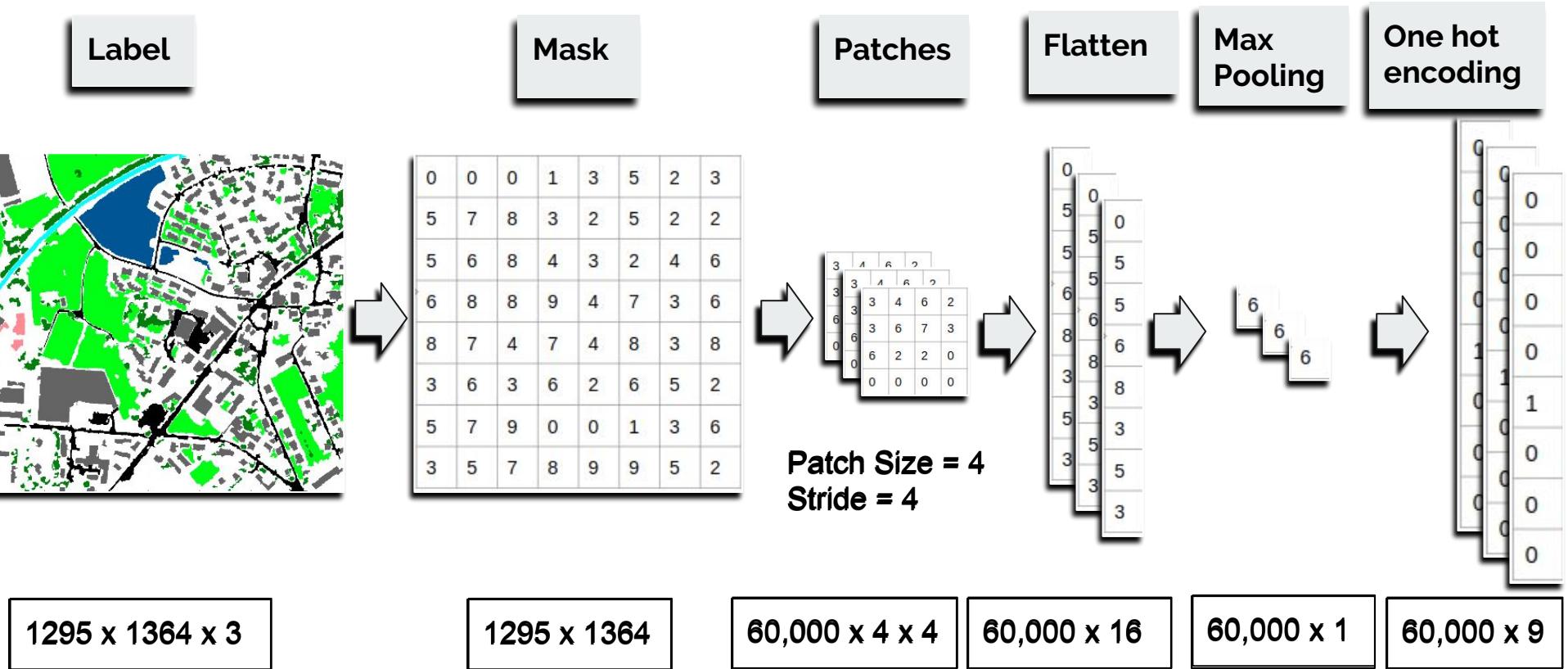


Patch Size = 4
Stride = 4



60,000 x 4 x 4 x 4

Actual Label Processing



CNN Architecture

4 X 4 X 4

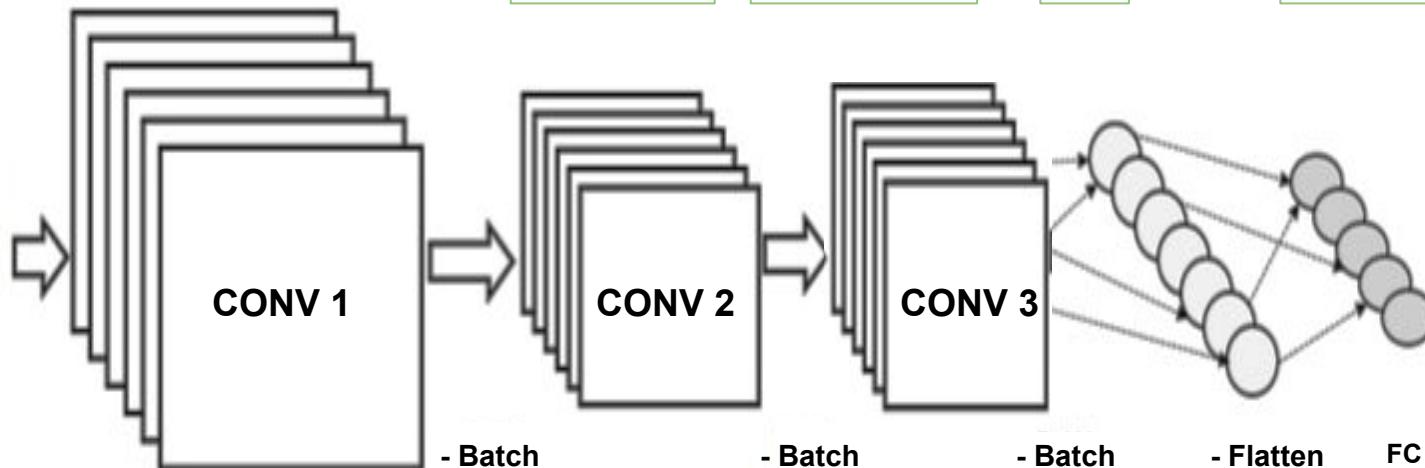
4 X 4 X 64

2 X 2 X 64

2 X 2 X 128

128

9 Classes



CONVOLUTIONAL
LAYER 1

NO. OF FILTERS = 64
FILTER SIZE = 1 x 1
STRIDE = (1,1)

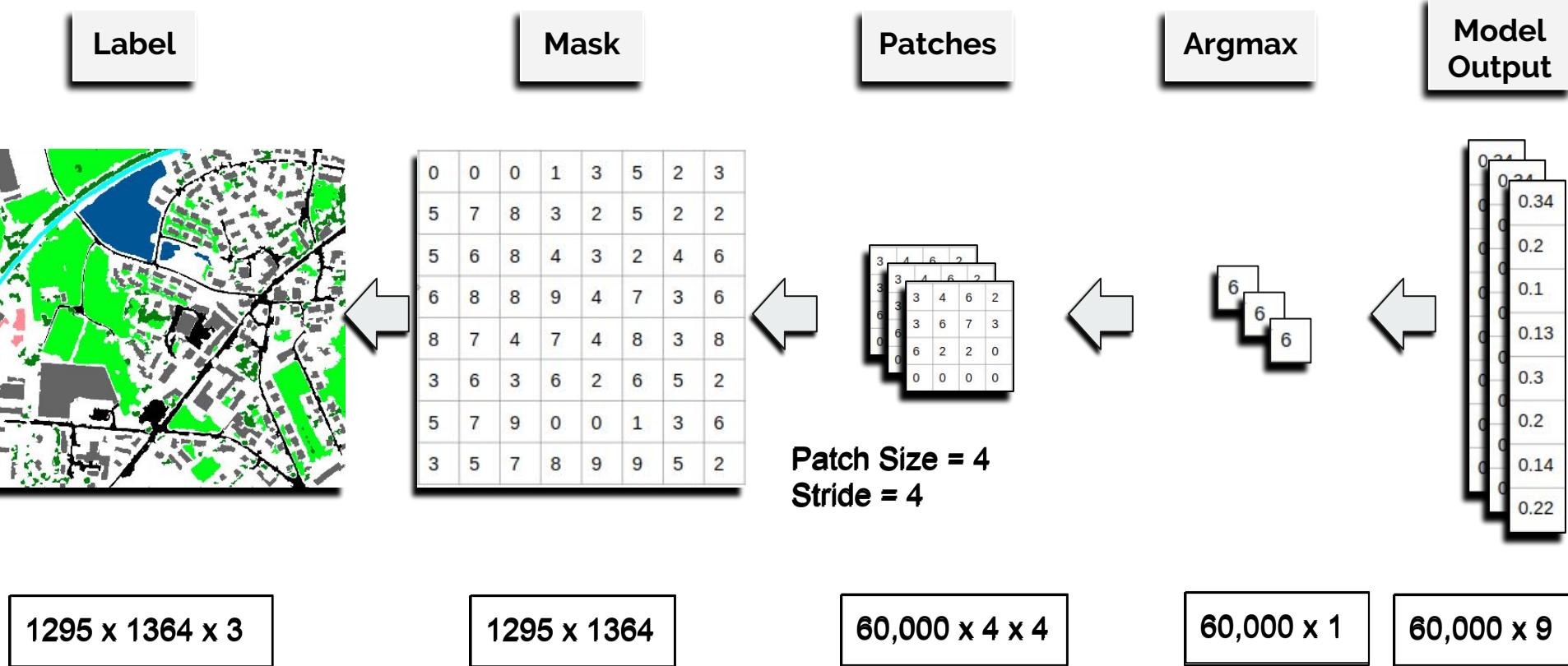
CONVOLUTIONAL
LAYER 2

NO. OF FILTERS = 64
FILTER SIZE = 1 x 1
STRIDE = (1,1)

CONVOLUTIONAL
LAYER 3

NO. OF FILTERS = 128
FILTER SIZE = 3 x 3
STRIDE = (3,3)

Predicted Label Processing



Batch Normalization

- Allows higher learning rates
- Faster in training
- Easier to initialise as weight initialisation can be difficult
- Helps reduce the sensitivity to the initial starting weights

Regularization method

- **Dropout technique** to reduce overfitting
- Prevent complex co-adaptations on training data
- Efficient way of performing model averaging with neural networks

The term "dropout" refers to dropping out units (both hidden and visible) in a neural network.

Cross-validation

- How accurately a predictive model will perform in practice
- K-fold cross validation and so as to prevent model from biasing toward any particular validation set.
- Ensemble model to create more generalised model and predicted output.

Data Augmentation

- Useful if number of images is less
- Increase the training data and make it more efficient

White Classification

As we know that white colour represents “**NO CLASS**” label i.e. the area represented by the pixels is not known.

- By increasing the Alphawhite variable in the code, we can decrease the False-positive of No Class (White).

Callbacks

- **Checkpoints**
- **EarlyStopping**
- **ReduceLROnPlateau**

Fixing bugs more quickly

Easier to visualise the model's training

Prevent overfitting by customizing the learning rate on each iteration.

Checkpoints:

Save the latest best model according to the quantity monitored

EarlyStopping:

Save time as training will stop if the model doesn't show improvement

Restore model weights from the epoch with the best value of the monitored quantity.

ReduceLROnPlateau:

Reduces the learning rate by a factor of 2-10, once learning stagnates.

Predicted Output

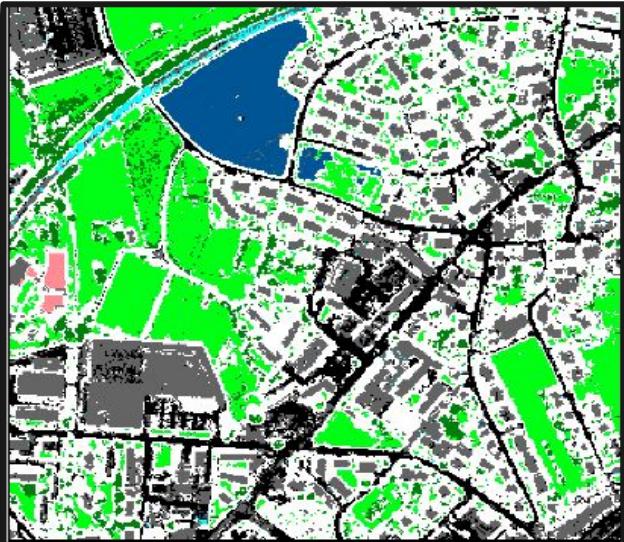


- No Class
- Buildings
- Road
- Grass
- Trees
- Railways
- Bare soil
- Swimming Pool
- Water

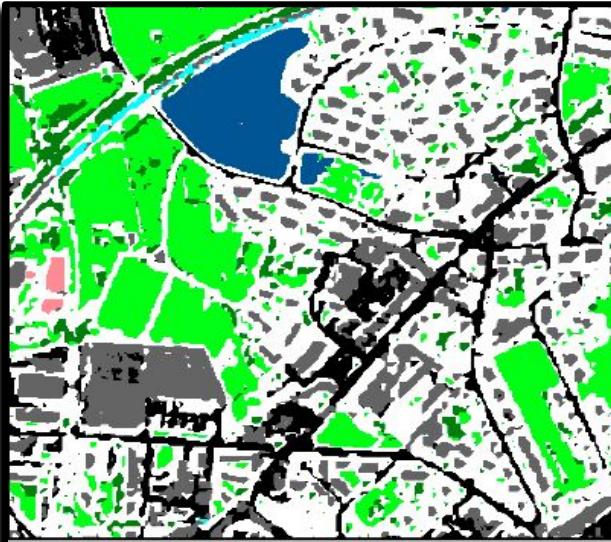
Smoothen The Predicted Images

For better visualization, we smoothen the predicted image from our model by running max pooling with $(1,1)$, $(3,3)$ and strides in $\{1,2,3\}$.

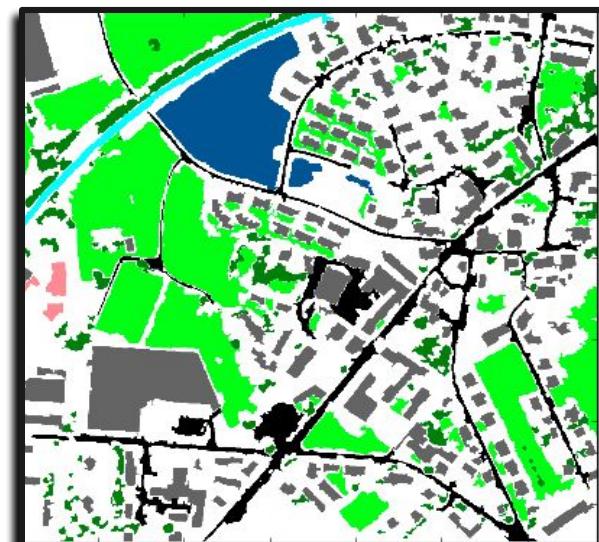
Predicted



Smoothen the
Predicted



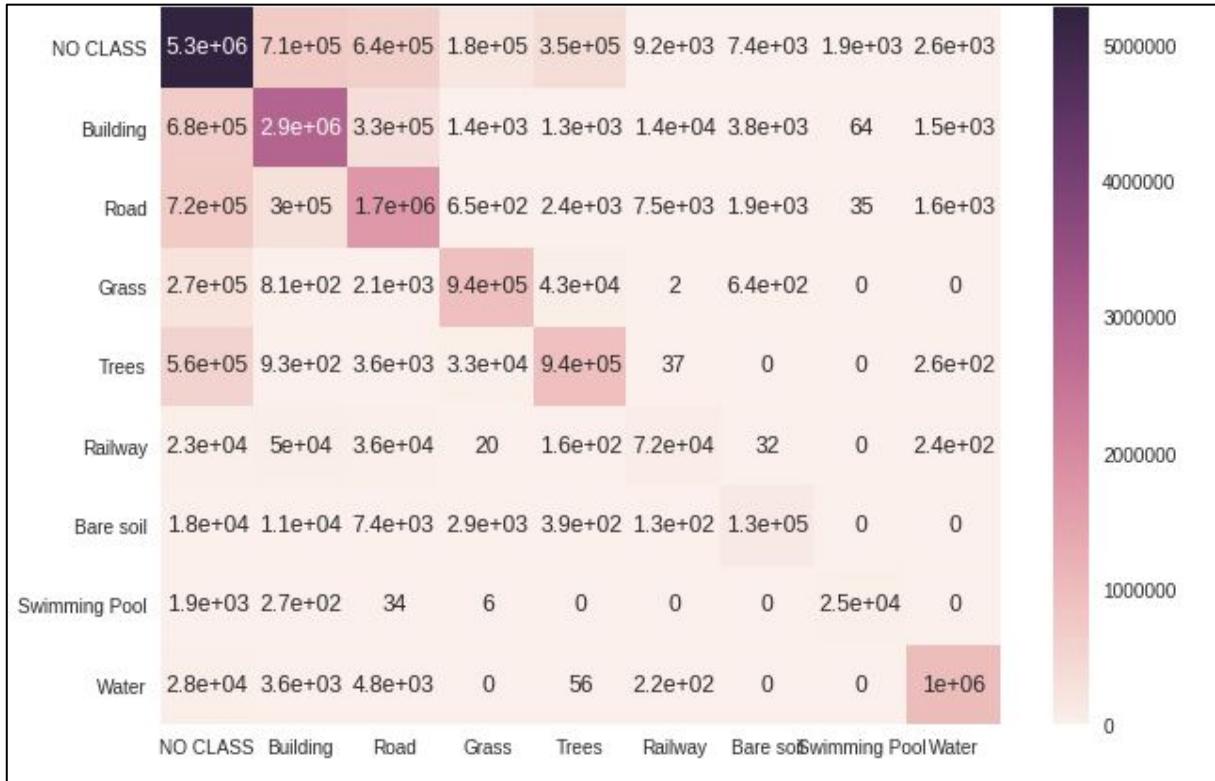
Actual Label



Evaluation

Kappa Coefficient (Complete Training Set) = 0.6239605778685826

Overall Accuracy (Complete Training Set) = 71.8548083657535%



The Classification Report is as follows:

ID	Precision	Recall	f1-Score	Support
0	0.70	0.73	.71	7206476
1	0.73	0.74	0.73	3969240
2	0.63	0.62	0.62	2758133
3	0.81	0.75	0.78	1248652
4	0.70	0.61	0.65	1542719
5	0.70	0.40	0.51	181611
6	0.90	0.77	0.83	169284
7	0.93	0.92	0.92	27473
8	0.97	0.96	0.97	1037898
Micro Average	0.72	0.72	0.72	18141486
Macro Average	0.79	0.72	0.75	18141486
Weighted Avg	0.72	0.72	0.72	18141486

train_loss vs val_loss

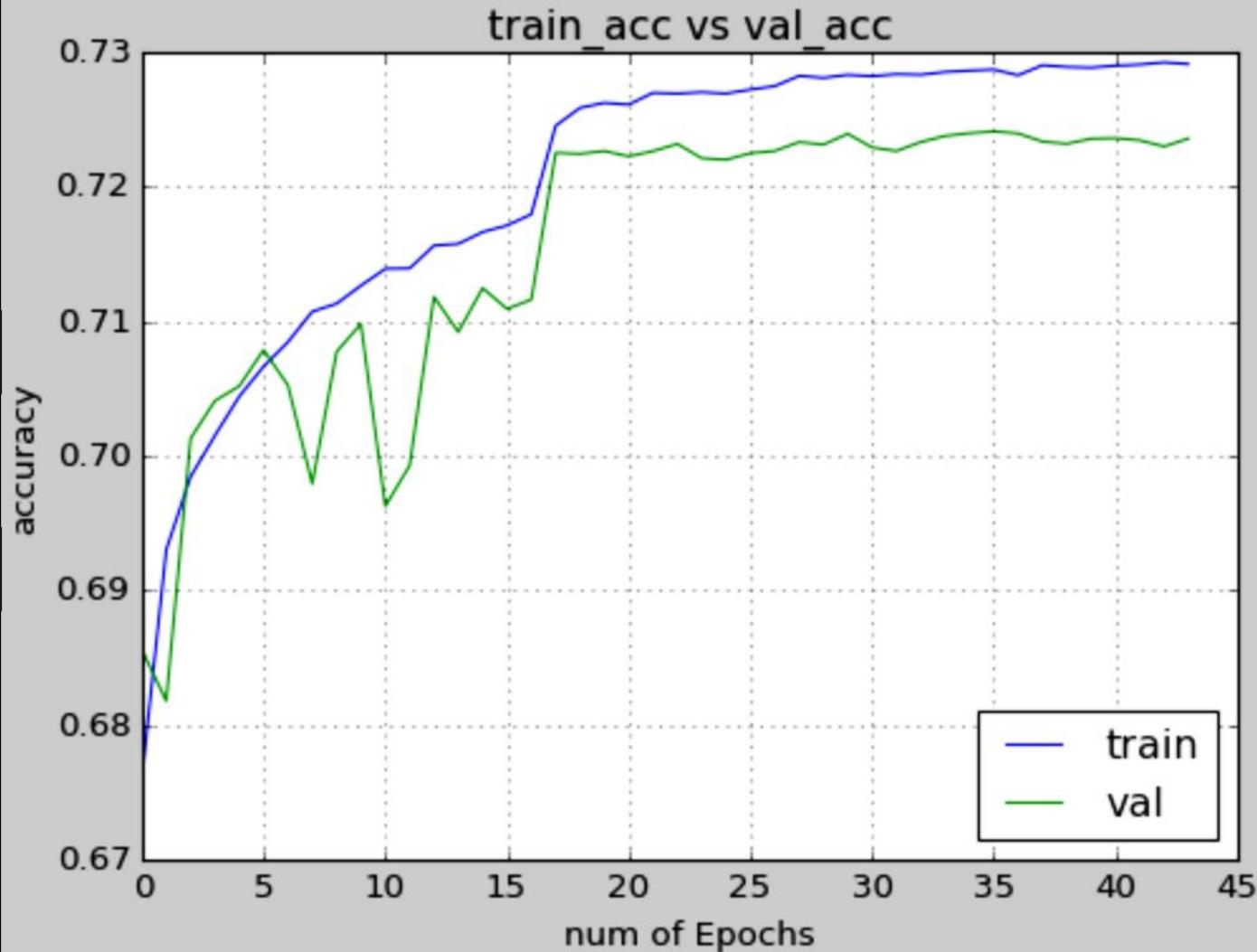
Training Loss

V/s

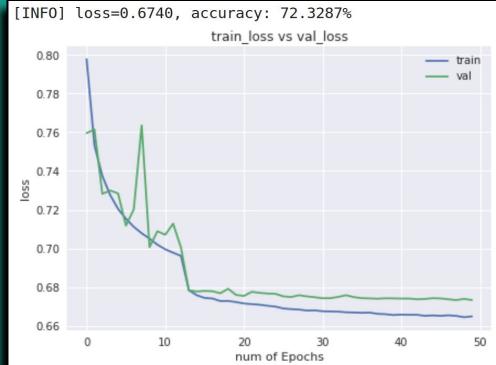
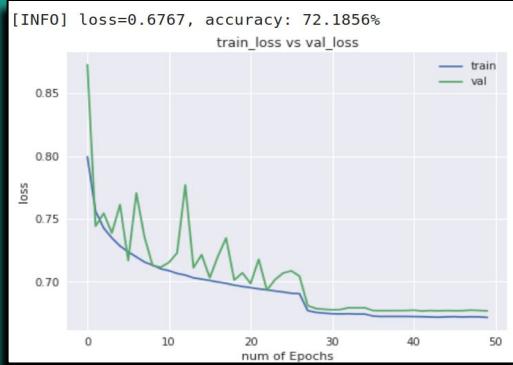
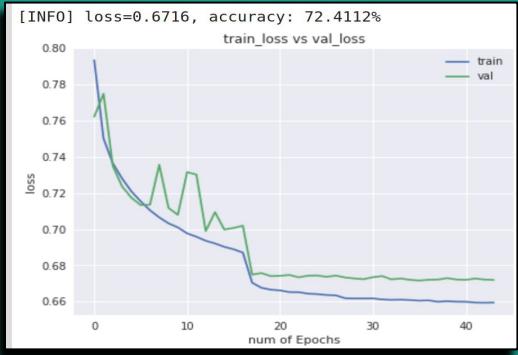
Validation Loss



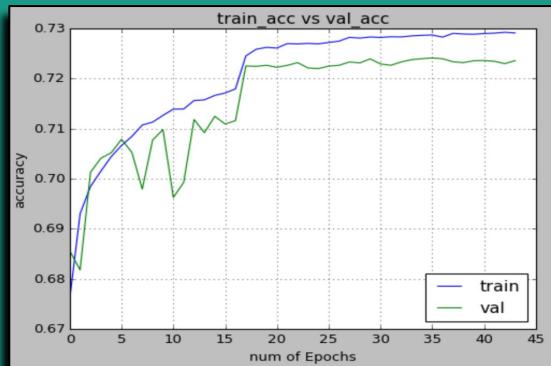
Training Accuracy
V/s
Validation Accuracy



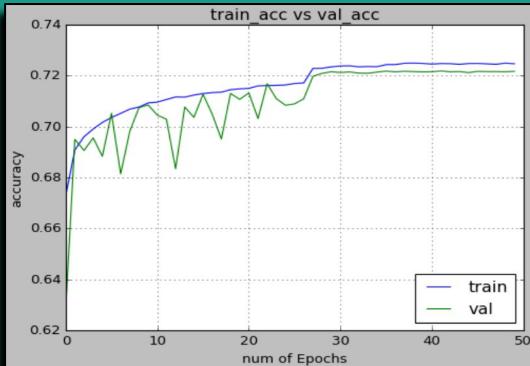
Different Optimizers



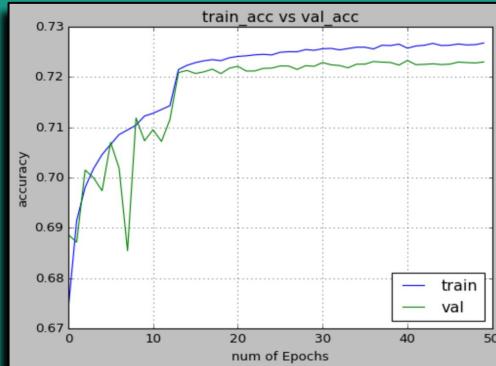
Nadam



Adadelta



Adam



We chose Nadam, Since it is stochastic optimization method, which trains quickly on big data. It is Adam RMSprop with Nesterov momentum.

Conclusion

A photograph showing a close-up of a person's hands. One hand holds a pen and is writing in a notebook. The other hand is resting on the table. The person is wearing a light-colored shirt with a small logo on the chest. The background is slightly blurred.

Satellite imagery hold a large amount of information. However, to use this information, it needs to be extracted from the raw image data. Object recognition is a method that can help the extraction of information from satellite images. Supervised object recognition approach was chosen based on the performance based on the quality of the spectral data and the number of classes. The CNN based model was then trained on the satellite images. The results based on different parameters, optimizers, learning rate and callbacks suggested that above model yields better performance with the testing dataset. This study can be explored in future research to see how the results are affected if the feature selection is done based on more number of training set and by using data augmentation.

The Team



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