

FARIS DZIKRUR RAHMAN // APRIL 2020

# RICE FIELD PREDICTOR



Employing SSD Object Detection Algorithm to Predict  
Rice Field in Banyuwangi Region

# Presentation Highlights

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01

## Executive Summary

Purpose, How It's Done,  
Project Question, Benefit to  
Policy Maker

02

## Workflow

Collecting training data,  
preparing the data, exporting  
training data, training model

03

## Conclusion

Accuracy, comparison,  
insight to policy maker



# Executive Summary

Background | Purpose | How It's Done | Project Question | Benefit to Policy Maker



# PROJECT BACKGROUND



## Agrarian Society

Indonesian people is widely known as an agrarian society.



## Important economic foundation

Many people still rely on rice field as their main financial source and most precious assets.



## Massive Development

Massive development of buildings and roads make people start losing their own rice field.



# Purpose

**01** Automatically understand the proportion of rice field in one village / area

**04** Automate the work of counting and detecting rice field in one area

**02** Using satellite imagery to know how many rice field that cover each area

**05** Combining the power of ArcGIS Pro and Python 3 to build the model

**03** Utilize object detection deep learning algorithm



# Location of the Analysis



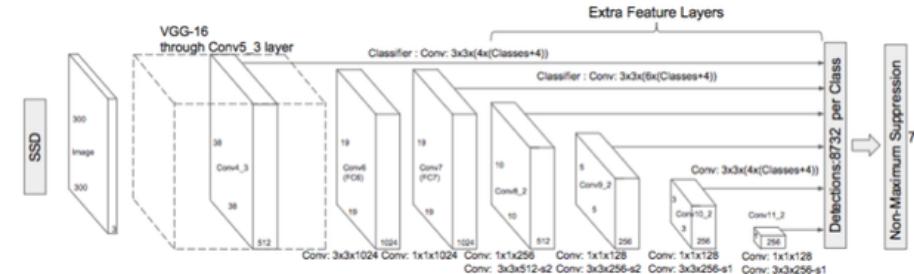
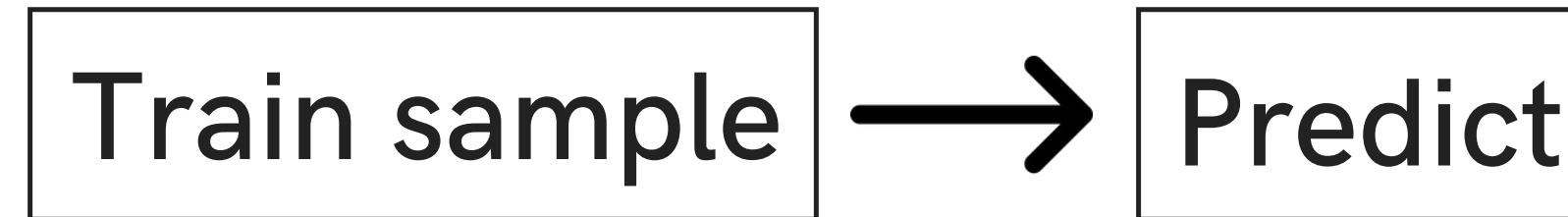
## Why Banyuwangi?

Balance proportion between object of four classes

Constitute of rice field, houses, roads, and trees

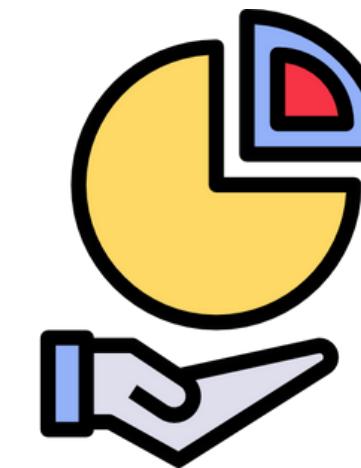


# HOW IT'S DONE





# Project Question



Proportion of  
each classes



Model  
performance



# BENEFIT TO POLICY MAKER

Insight on proportion of rice field in particular region

Comparison with previous year

Understand density of housing condition

Ease the process of analysing satellite imagery to extract information



# Workflow

Collecting Training Data | Preparing The Data | Exporting Training Data | Training Model



# Methods Used

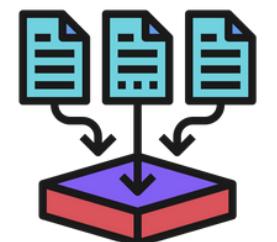


**arcgis.learn**



- Training data could be fed directly to deep neural network
- Adopt state of the art research in deep learning subject (fine tuning)
- Adopt fast.ai framework to know learning rate before fitting the model
- Integration with ArcGIS platform





# COLLECTING TRAINING DATA

Use Label  
Objects for  
Deep Learning  
Tool



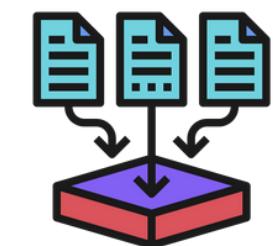
Label Objects for Deep Learning

Create and manage labeled objects for deep learning.



Save data as  
**image chips** to  
a folder





# COLLECTING TRAINING DATA (2)

Map X

Image Classification

Label Objects : 5da45f5336266f000578cc3b... ☰

Banyuwangi\_Field

- Paddy Field
- House
- Road
- Trees

Labeled Objects Export Training Data

Class	Pixels (%)
Paddy Field	2,13
Paddy Field	1,48
Paddy Field	1,64

Run

Class Pixels (%)

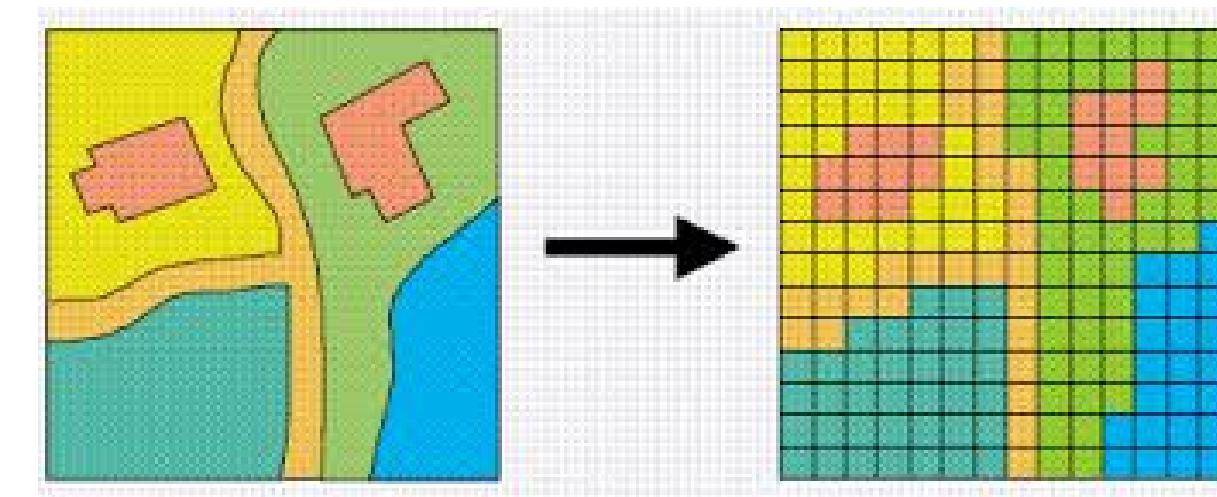
Paddy Field 2,13

Paddy Field 1,48

Paddy Field 1,64

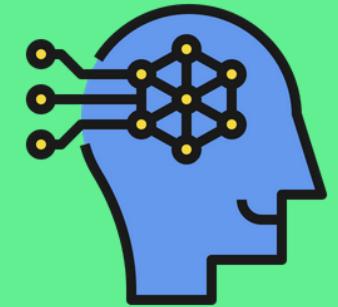


# PREPARING THE DATA



Object must be  
surrounded  
inside  
bounding box

Bounding box must  
include **raster layer**  
containing  
information of **pixel**  
and **band**



# TRAIN THE MODEL

01

Build SSD  
Model

02

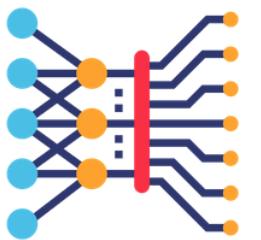
Determine  
learning rate

03

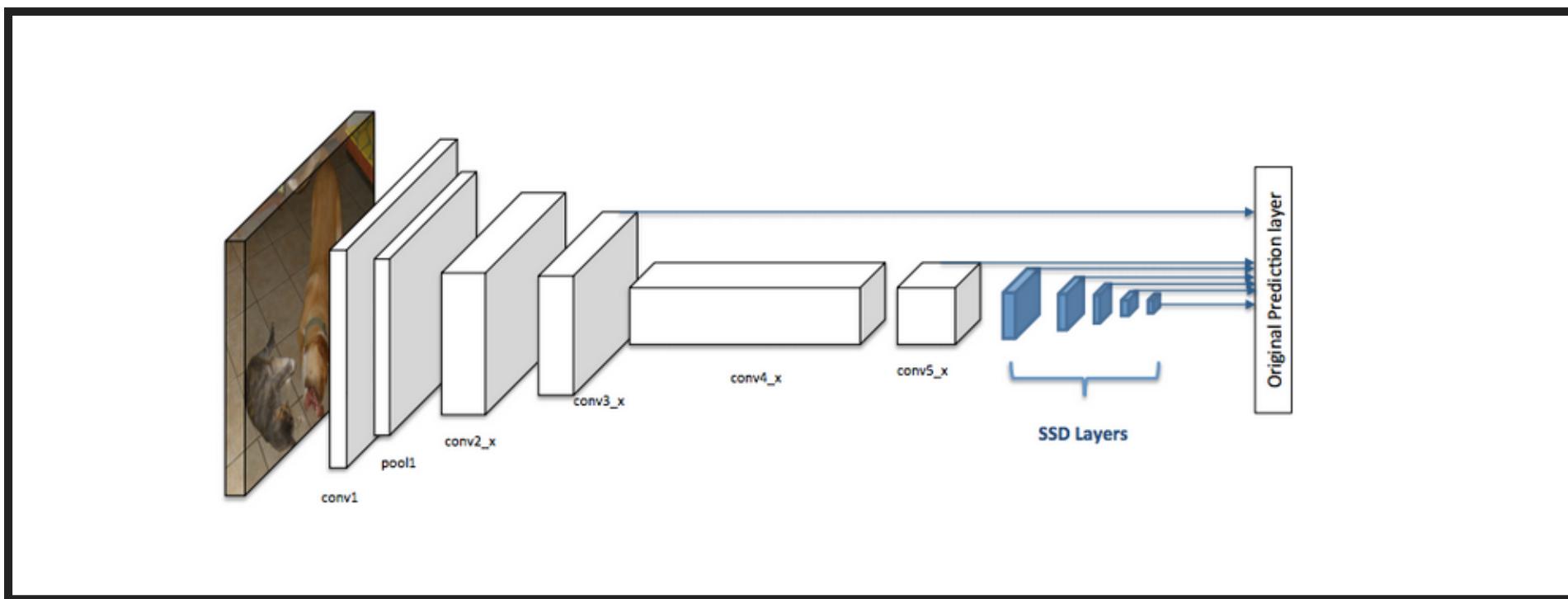
Fit the model

04

Visualize in  
validation set



# BUILD SSD MODEL

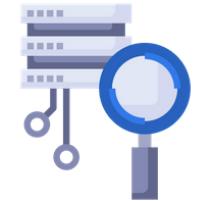


Backbone model

ResNet

SSD head

Additional  
Convolutional layer



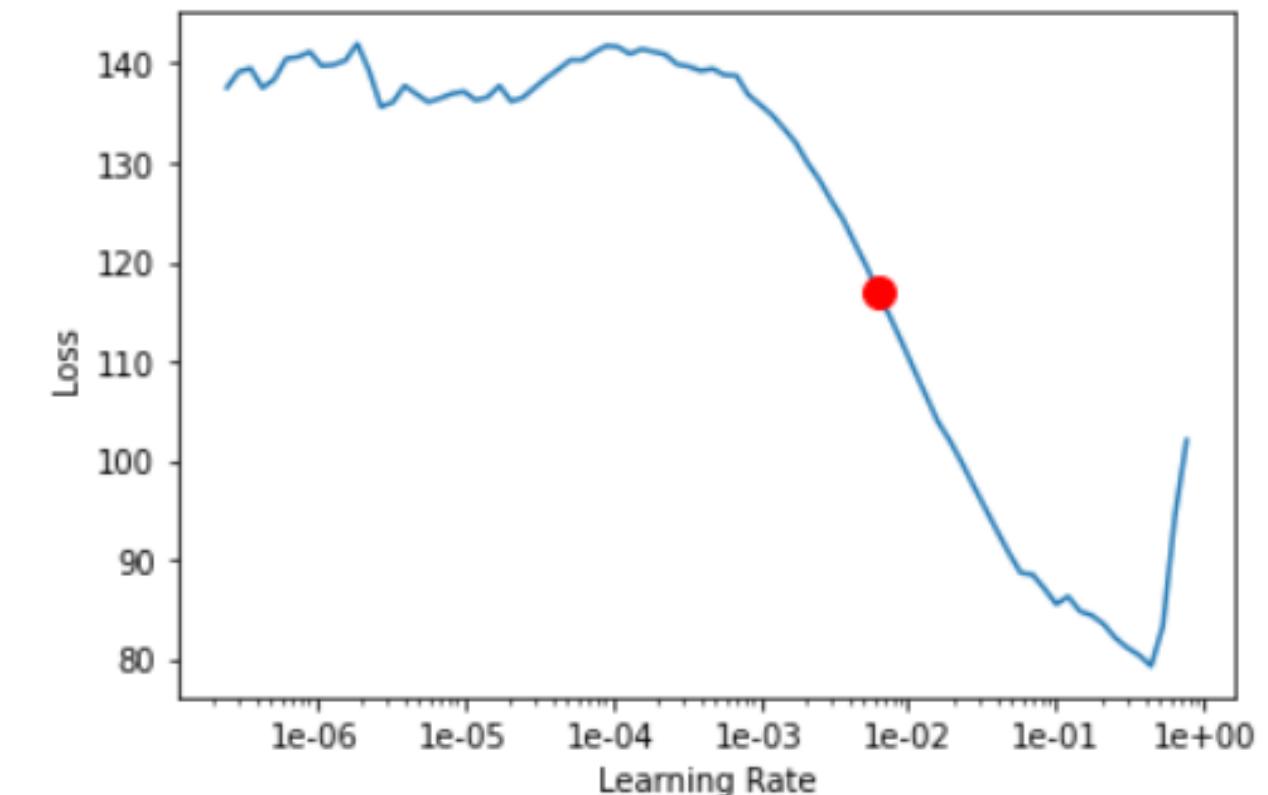
# DETERMINING LEARNING RATE

The most important part of **hyperparameter tuning**

control how many **change** should be made by model to  
**tackle the error** everytime model weights are updated

Use **lr.find()** method from `arcgis.learn`

learning rate = 0.006





# FIT THE MODEL

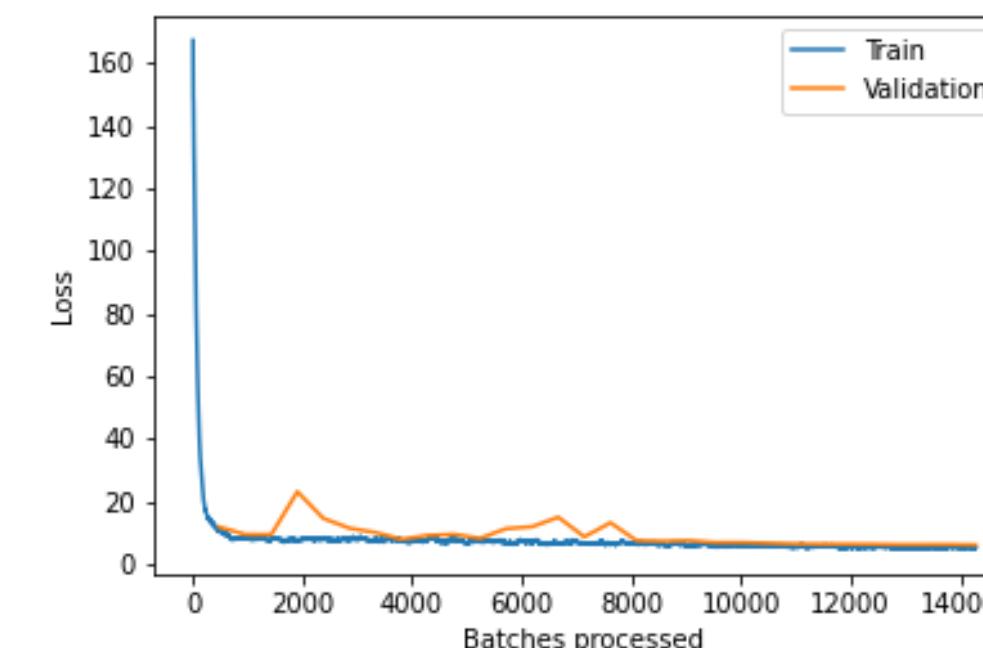
```
model.fit(epochs = 30, lr = 0.006)
```



loss table

epoch	train_loss	valid_loss	time
0	10.315011	11.733285	06:37
1	8.113664	9.358253	06:47
2	7.934251	9.320403	06:44
3	7.289202	23.042048	06:44
4	7.615413	14.468821	06:49
5	7.603299	11.346416	06:48
6	7.834518	9.946873	06:50
7	7.511830	7.811392	06:47
8	7.941373	9.044391	06:48
9	7.663841	9.387100	06:37
10	6.969141	8.132494	06:36
11	6.616311	11.194818	06:35
17	6.267069	7.189839	06:38
18	5.962504	7.379387	06:39
19	5.827171	6.793268	06:37
20	6.217280	6.798838	06:36
21	5.887025	6.581117	06:35
22	5.392021	6.367720	06:33
23	5.823403	6.286198	06:26
24	5.224324	6.270298	06:22
25	5.385494	6.245301	06:21
26	4.911328	6.133076	06:19
27	4.997423	6.138157	06:30
28	5.394149	6.147987	08:54
29	5.199675	6.023864	10:18

loss graph



# MODEL PRECISION SCORE

Precision is how precise/accurate your model is out of those predicted positive, how many of them are actual positive.

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}$$



Rice Field = 81%



Houses = 34%



Trees = 55%



Roads = 53%

Rice field shows pretty fair result of precision due to the amount of data that is collected

Other class seems to lack in precision due to the insufficient sample data

# VISUALIZE IN VALIDATION SET

show the **prediction result** hand in hand with the ground truth, so that we could get the picture on how our model perform compared to ground truth.



# Conclusion

Fair result of precision on rice field class

Good comparison between ground truth and prediction

Can be used by policy maker to leverage the well being of society

# THANK YOU



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