Semantic Segmentation for Field Delimitation using Neural Networks

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01. Introduction

Objectives of the study

1. To achieve the optimal semantic segmentation of field boundaries by training neural networks.
2. To set up a benchmark in accurate boundary extraction from earth observation images.
3. To set up a complete workflow which would convert the raw geotiff images to field boundary polygon shapefiles.
4. To help farmers achieve sustainable development through precision farming practices.

Significance of the Study

- The awareness of location of fields on the farms is of great importance to a farmer
- Knowing the partition of the fields by their serial number or name can significantly improve the management of fields especially when it is reaping season.
- Also, the shapefiles of predicted boundaries can be integrated with a precision farming platform through which farmers can keep a track of all the activities taking place in all their fields.
- The automation of an extremely time consuming task such as field delineation will drastically improve precision farming practices.

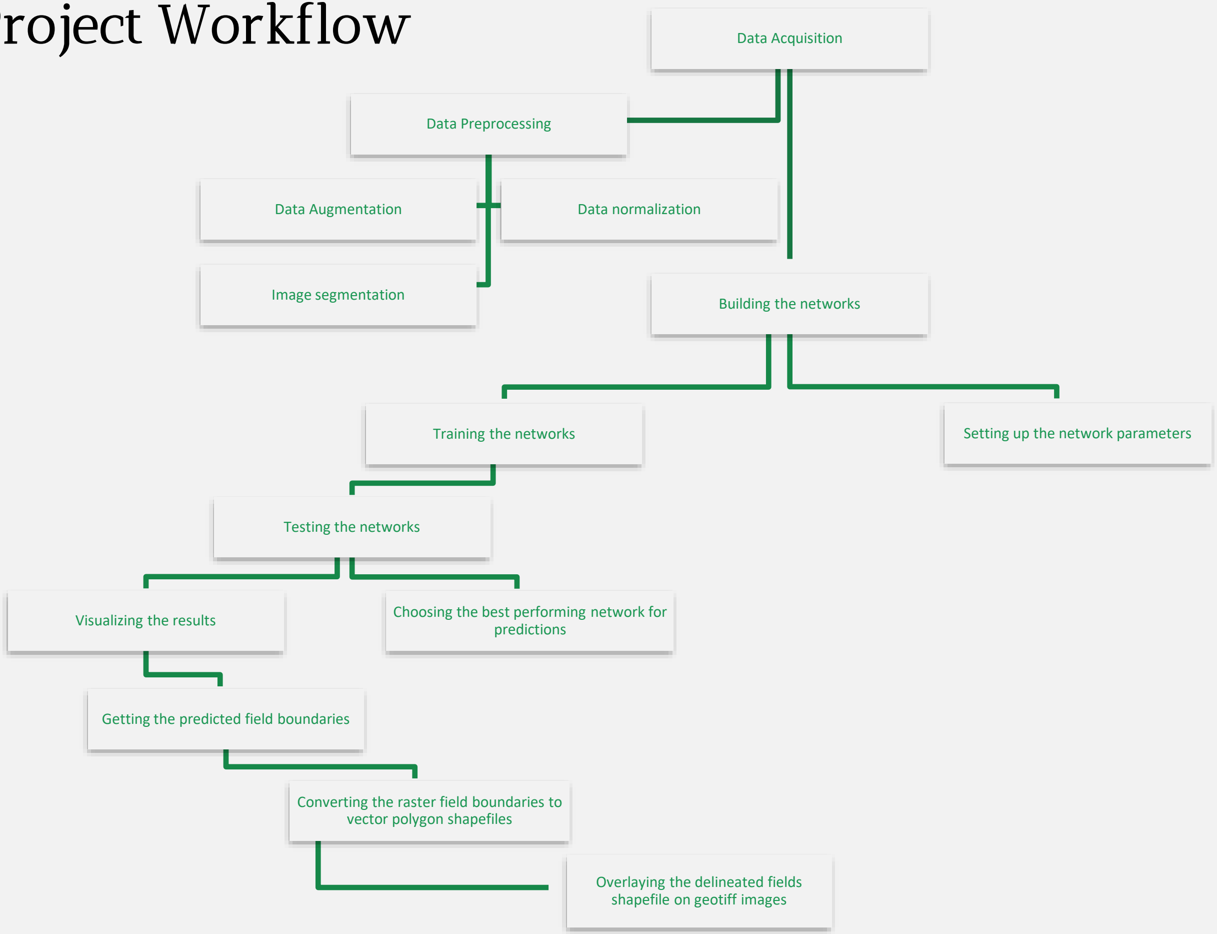
Study Area

- The study area is chosen as the Netherlands due to the availability of precise fields which was expected to help train the neural network.
- Around 122 image tiles are utilized which are distributed according to the abundance of fields.
- The figure aside which was processed on ArcGIS shows the distribution of fields is shown on the map of the Netherlands.

02 Methodology

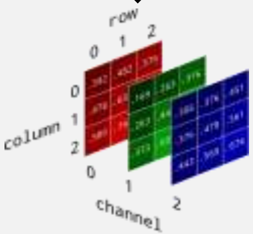
Project Workflow, Model Development

Project Workflow

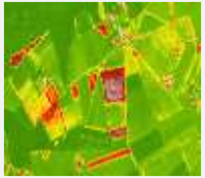


Data Preprocessing

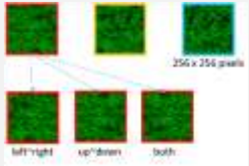
1. Converting Images into Pixel Wise Arrays



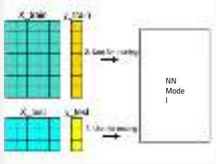
2. Normalizing the image



3. Dividing the images into smaller patches



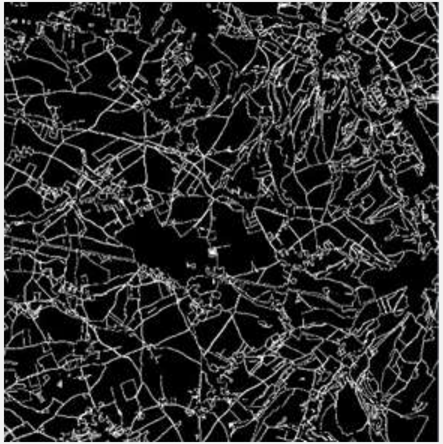
4. Setting up training and testing data set



Data Preprocessing

Original GeoTiff

GroundTruth of Boundaries

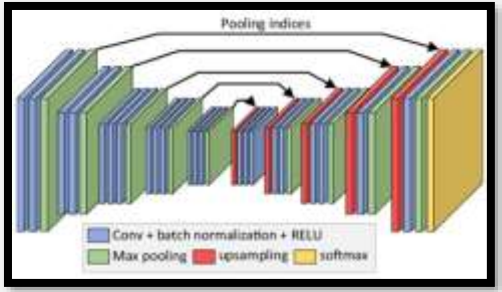


Overlayed

Model Architectures

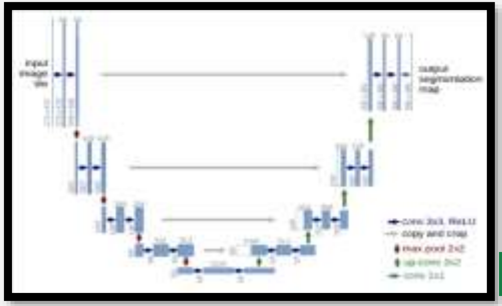
Fully Connected Network

- FCNs are made to automatically deduce pixel-wise estimates, irrespective of the quality of the source images.
- The decoder would be used to convert the encoder's reduced feature maps toward the input image's native resolution.



Unet

- One of the major advantages of UNet over FCN is its ability to detect features from a low-resolution image and give good results.
- UNet can work with a larger sample size at a time rather than dividing the samples into smaller sizes while training.



03

Results

Network Parameters

Network Name	Epochs	Batch Size	Patch Size	Learning Rate
Fully Convolutional Network 5	50	8	40000 px	0.1
	800	32	2500 px	0.0015
Fully Convolutional Network 6	50	8	40000 px	0.1
	800	32	2500 px	0.0015
Unet 2	50	8	40000 px	0.1
	800	8	160000 px	0.0015
Unet 3	50	8	40000 px	0.1
	800	8	160000 px	0.0015

Models trained

1 — Unet 2

Unet architecture with 2 layers

Gave accuracy of 91 percent

2 — Unet 3

Unet Architecture with 3 layers

Gave accuracy of 95 percent

3 — Fully Convolutional Network 5

CNN architecture with 5 layers

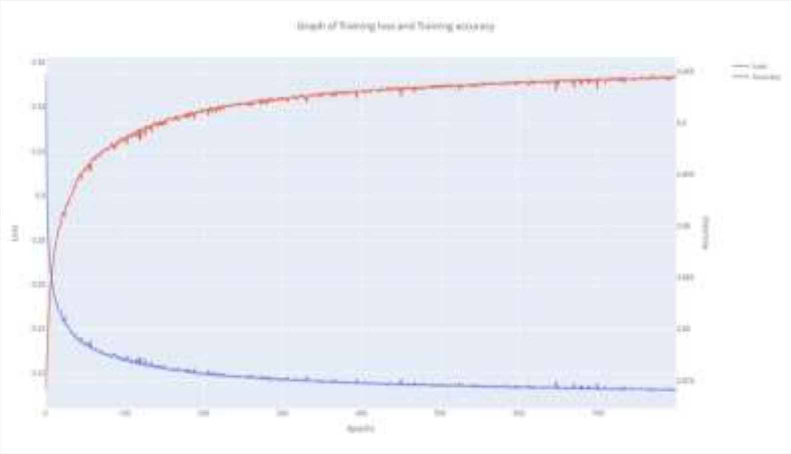
Gave accuracy of 84 percent

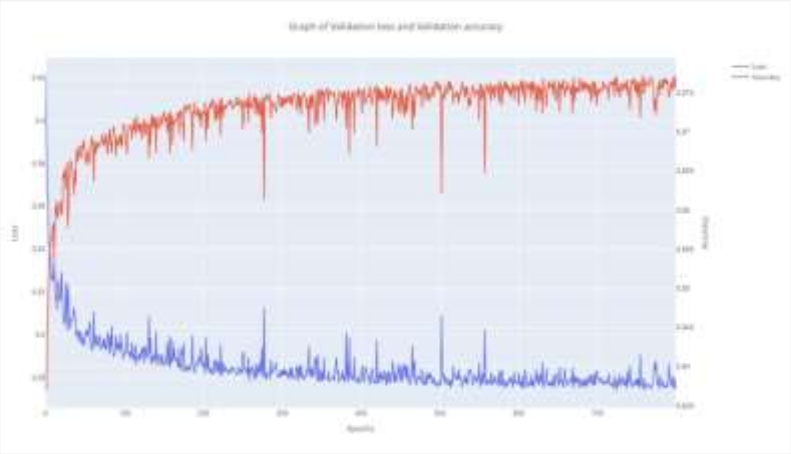
4 — Fully Convolutional Network 6

CNN architecture with 6 layers

Gave accuracy of 89 percent

FCN 5 Performance Visualized

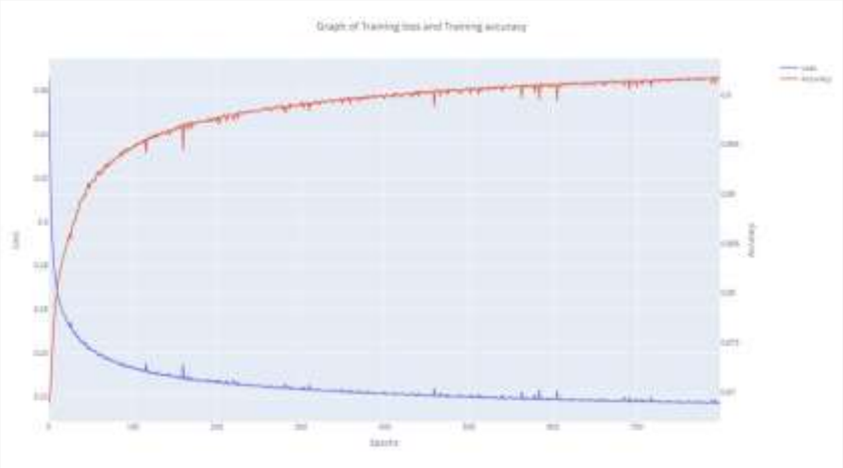


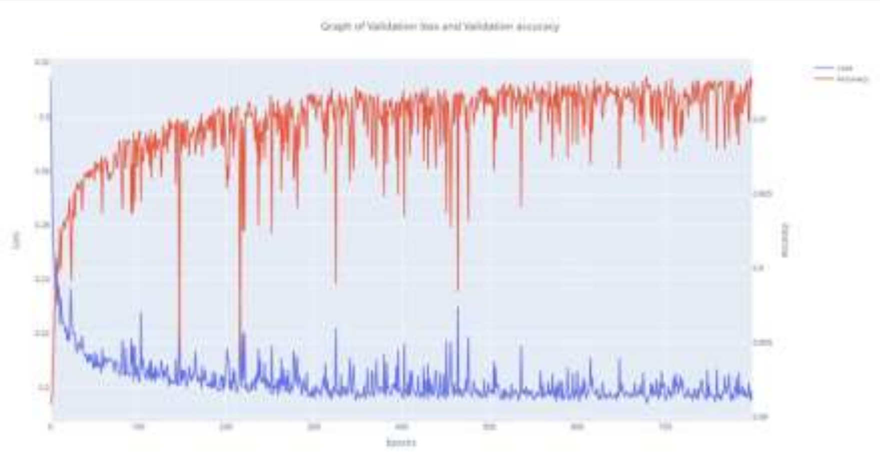


Training loss vs
Training accuracy

Validation loss vs
Validation accuracy

FCN 6 Performance Visualized

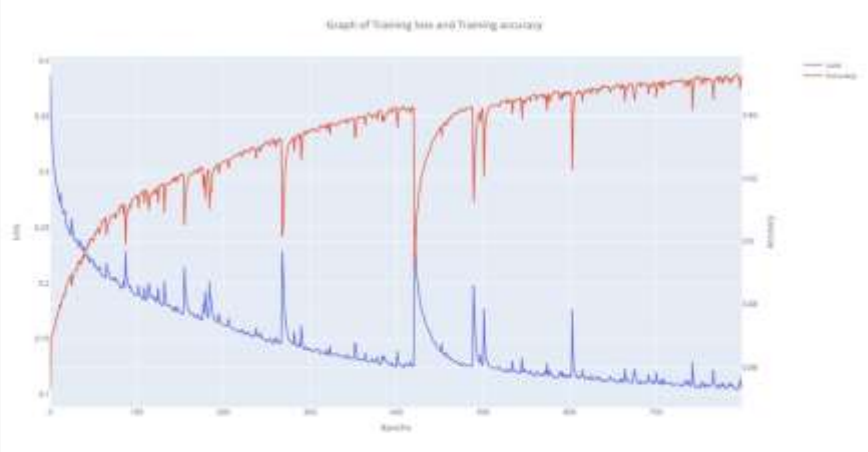




Training loss vs
Training accuracy

Validation loss vs
Validation accuracy

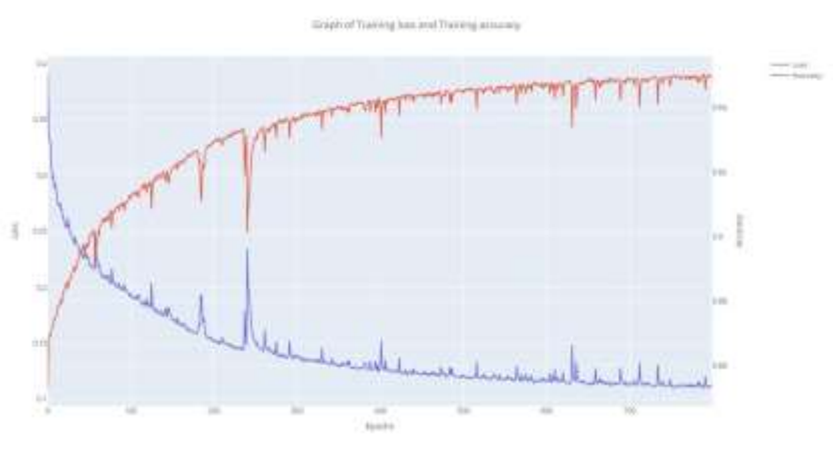
Unet2 Performance Visualized

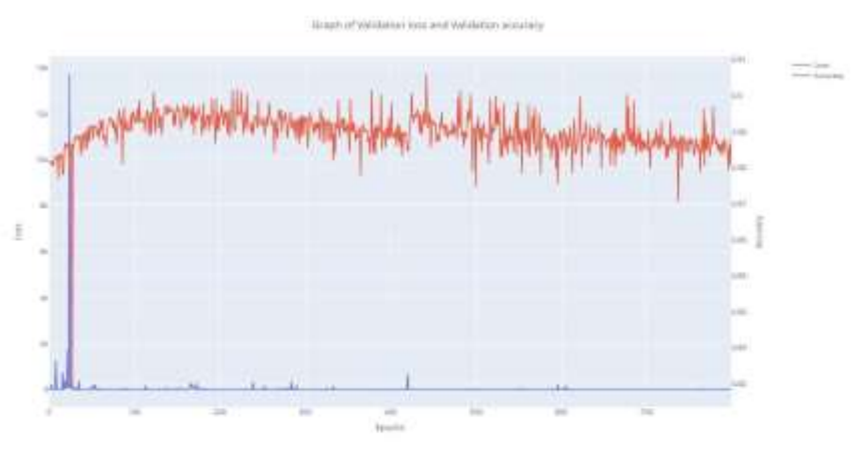


Training loss vs
Training accuracy

Validation loss vs
Validation accuracy

Unet3 Performance Visualized





Training loss vs
Training accuracy

Validation loss vs
Validation accuracy

FCN 5 and FCN 6 Performance Evaluated

	Actual Other	Actual Field Boundary	Sum
Prediction Other	473114 (73.924%)	58429 (9.13%)	531543
Prediction Field Boundary	30112 (4.705%)	78345 (12.241%)	108457
Sum	503226	136774	

Overall Accuracy	86.165	%
Precision	72.236	%
Recall	57.281	%
F1 Score	63.895	%

Fully Convolutional Network with 5 layers Evaluation

	Actual Other	Actual Field Boundary	Sum
Prediction Other	494174 (77.215%)	34878 (5.45%)	529052
Prediction Field Boundary	30786 (4.81%)	80162 (12.525%)	110948
Sum	524960	115040	

Overall Accuracy	89.74	%
Precision	72.252	%
Recall	69.682	%
F1 Score	70.944	%

Fully Convolutional Network with 6 layers Evaluation

UNet 2 and Unet 3 Performance Evaluated

	Actual Other	Actual Field Boundary	Sum
Prediction Other	532454 (83.196%)	31397 (4.906%)	563851
Prediction Field Boundary	26817 (4.19%)	49332 (7.708%)	76149
Sum	559271	80729	

Overall Accuracy	90.904	%
Precision	64.784	%
Recall	61.108	%
F1 Score	62.892	%

Unet2 Evaluation

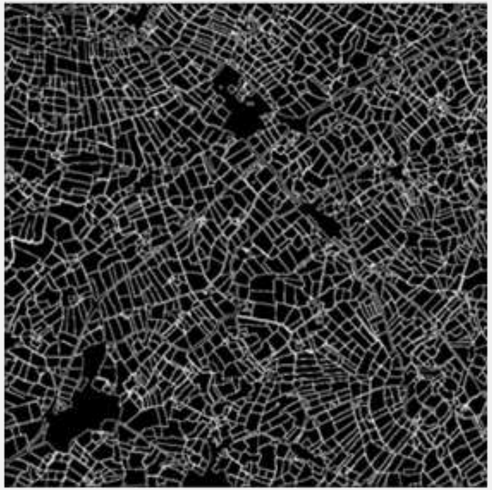
	Actual Other	Actual Field Boundary	Sum
Prediction Other	584522 (91.332%)	15354 (2.399%)	599876
Prediction Field Boundary	15787 (2.467%)	24337 (3.803%)	40124
Sum	600309	39691	

Overall Accuracy	95.134	%
Precision	60.654	%
Recall	61.316	%
F1 Score	60.984	%

Unet3 Evaluation

FCN 5 Predictions

Original GeoTIFF



Ground Truth

Prediction

FCN 6 Predictions

Original GeoTIFF

Ground Truth

Prediction

Unet 2 Predictions

Original GeoTIFF

Ground Truth

Prediction

Unet 3 Predictions

Original GeoTIFF

Ground Truth

Prediction

04 Conclusions

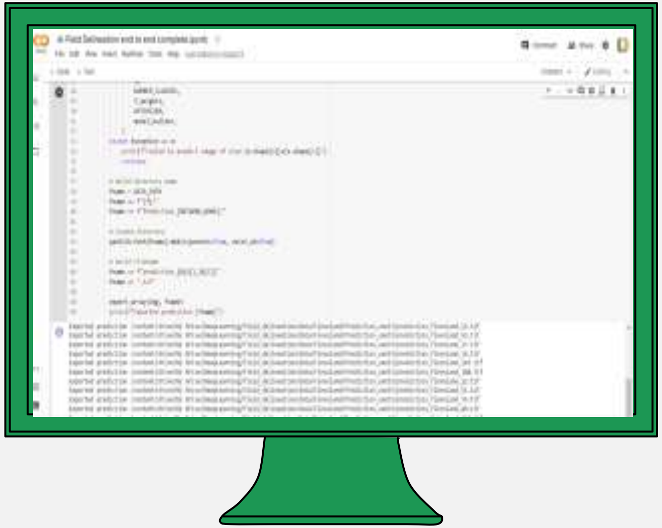
Field boundaries prediction System

Boundary Detection using **Unet3** Neural Network

- Unet3 is chosen for prediction of boundaries as it gives much more accuracy over fully connected neural network

- The network can automatically give the predicted field boundaries in tiff format to the specified output path.

- The clear advantage is that the model can predict about **1,00,000** boundaries in just 10 seconds!



Sample of completely processed field boundaries

Accurate

Quick

API ready

Robust Batch Processing

Thank You!