Field Boundary Delineation applied to Danish agriculture

Overview

- Farmers often need to provide digital records of the field boundaries when being signed up by service providers.
- Such field-level delineation and assessment has largely been a manual, labour intensive task and is time consuming having its own limitations of updating large areas.
- In this project the goal was to be able to automate this process using a deep learning based approach using Sentinel-2 imagery from Danish agricultural fields.

Introduction |

- Recent years have seen a significant use of emerging technologies such as remote sensing in the field of precision agriculture.
- The Sentinel-2 satellite earth observation mission provides high resolution multi-spectral satellite imagery.

- These satellites have been widely used for a variety of applications such as land cover monitoring, forest monitoring, agricultural applications

- Further, the recent advancement in deep learning-based image analysis techniques and the sheer availability of high resolution satellite imagery has demonstrated considerable potential for automated delineation of these agricultural field boundaries thus motivating our problem statement.

Introduction II

- Previously edge based methods or region growing based methods which have been used for this purpose. However these methods rely on handcrafted features and parameter tuning using trial and error.
- Deep learning methods have shown promising results in image segmentation tasks.
- The problem of extracting field boundaries is treated as a multi-class segmentation problem. A ResUNet model is trained to output three labels for each pixel, i.e. probability of belonging to a field, boundary and the distance of each pixel to the closest boundary.

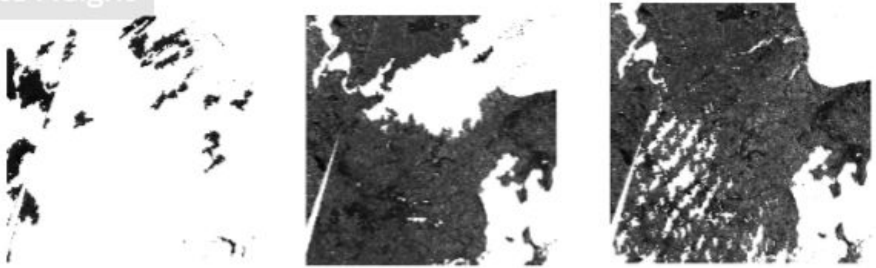
Data Description

- The data consists of sentinel-2 satellite images for the for the year 2020
- 6 tile sets covering different areas of Denmark. .
- Data from the months March-August, recorded over different months.
- Each such data-point is a multi-spectral image having 13 bands.
- RGB and Near Infrared (NIR) bands available to us at a resolution of 10980 × 10980 pixels, at a spatial resolution of 10m GSD.

Data Preprocessing

The following preprocessing steps were performed:

- Generating Monthly Median Composites
- Extracting extents, boundaries, and generating distance transforms.
- Z-Score Normalization
- Data Augmentation



(a) Overlayed images (01/03 - 03/3)

(b) Overlayed images (25/03 - 26/3)

(c) Overlayed images (25/03 - 26/3)

Figure 1: Images from tileset VNH over different days of the month of March

Figure 2: Monthly Composite Image

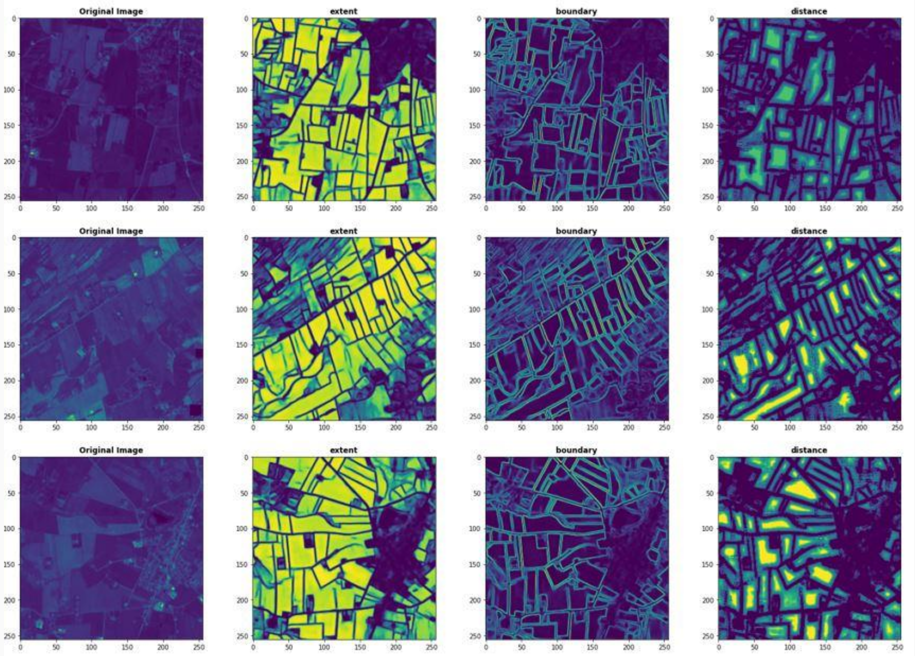
Methods I

Training, Testing, Validation:

- Out of the 6 tile sets available, 4 were used for training, 1 for validation and 1 for testing.

- The training set contains a total of 24 monthly composite images, that are used for generating the training crops

- From each image, we extract 2000 crops of size 256 X 256. The training set thus contains a total of 48000 (24 x 2000) training images, while the validation and the test set contained a total of 12000 such crops.



Methods II ResUNet Framework

- It is a deep convolutional neural network that was developed as an improvement to the existing UNET architecture, incorporating Residual network features to perform pixel-level multi-class segmentation.

- The RESUNET consists of an encoding network, decoding network and a bridge connecting both these networks

- It employs residual connections, convolutions and pyramid scene pooling and multi-tasking inference.

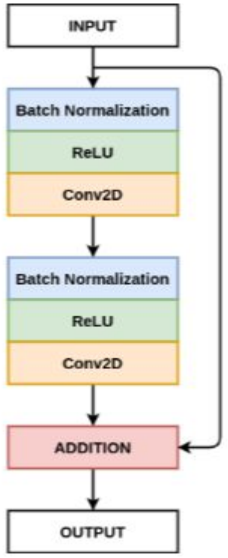


Figure 4: Residual Block

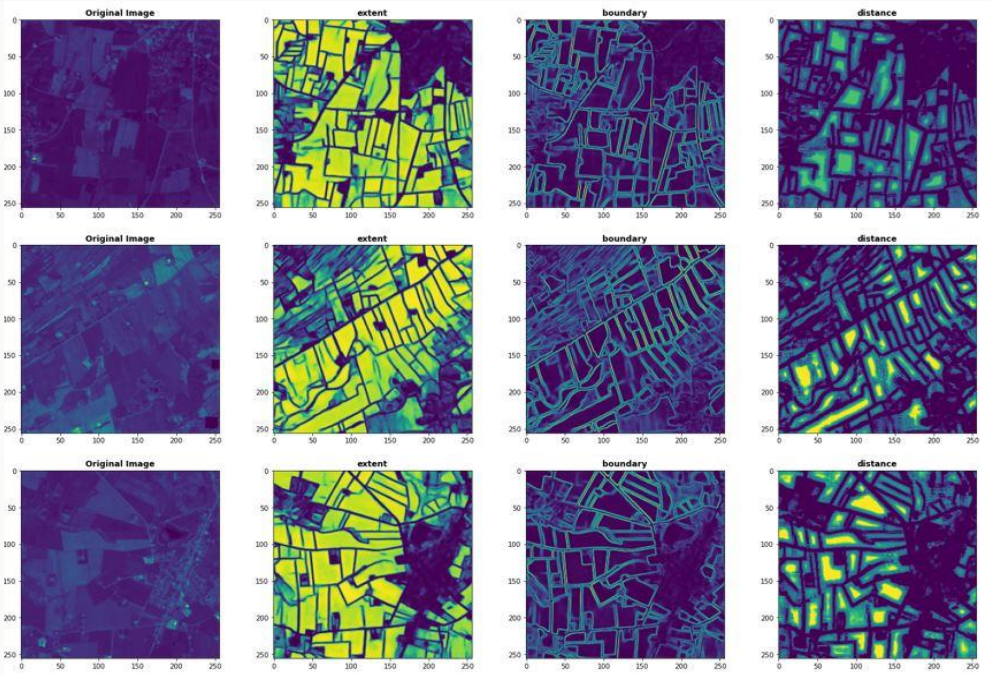
Methods |||

- The model was trained for 15 epochs or 120000 total steps, and validated for 30000 steps.
- Due to simplicity, Mean Squared Error was used as a loss function for all extents, boundary and distance predictions. In order to achieve training stability and boost generalization performance , a small batch size of 6, and the Adam Optimiser was used for training

Results

	Boundary	Extent	Distance
MSE Loss	0.1503	0.1536	0.137
Accuracy	0.8725	0.8052	0.9085
IOU	0.2545	0.2535	0.4309

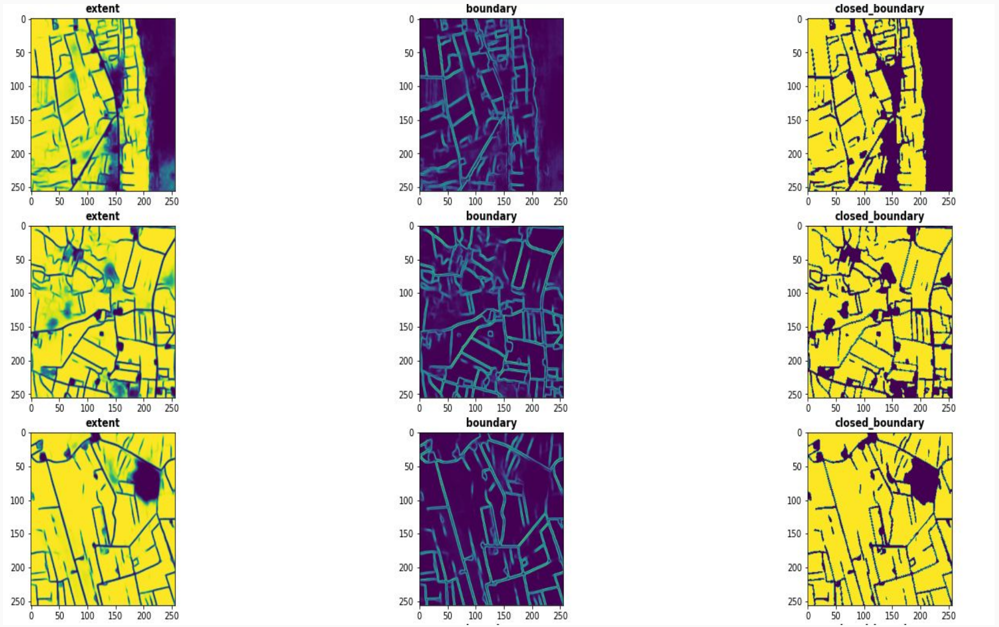
Table 1: Results



Results

Postprocessing:

- In order to fine-tune the predicted results and get generate closed boundaries, a simple thresholding based approach was used.
- .A variety of thresholds ranging between (0 and 1) in steps of 0.1 were tested for this purpose.
- In order to delineate individual fields, a threshold was applied to the extent mask and the boundary mask. The intuition is that the threshold on the boundary mask helps to define boundaries between adjacent fields whereas the threshold on the extent helps distinguish between ”field” and ”non-field” pixels.



Conclusion and Future Work

- A ResUNet model was applied to the problem of field boundary delineation.
- Preliminary results show an accuracy of 80% on test data.
- In terms of experiments, the model could be further trained for a larger number of epochs following a K-fold cross validation approach so that it is able to generalize well. Further, the MSE loss currently used takes into consideration the pixel wise difference.