Webology (ISSN: 1735-188X)
Volume 18, Number 6, 2021

Delineation Of Agricultural Field Boundaries Through A Cascaded Deep Network Model From Polarized SAR & Multispectral Images

Prof. Salunke Shrikant Dadasaheb, Prof. Bere Sachin Sukhadeo, Prof. Bhange Rajani Rahul , Prof. Kadam Swati Amol, Prof. Shende Sachin Santosh

Dattakala Shikshan Sanstha "Dattakala Group of Institution" Swami-Chincholi, Daund, Pune, Maharashtra 413130. India.

ABSTRACT

By combining multispectral imagery from Sentinel-1 and Sentinel-2 satellites with polarized Synthetic Aperture Radar (SAR), this research presents a cascaded deep network model for agricultural field border demarcation. The model uses a cutting-edge method that combines edge detection and semantic segmentation to improve the accuracy of recognizing agricultural boundaries. TensorFlow and PyTorch are used to create models in this study, which covers a wide range of geographical and climatic zones. Classification reports and Intersection-over-Union.

(IoU) scores are examples of evaluation metrics. The results demonstrate the usefulness of the model by giving accurate field boundaries that may be used in precision farming. Suggestions include integrating topographical data for improved accuracy, improving model design, and enriching datasets even further.

Keywords: Sentinel-1, Sentinel-2, IoU score, deep learning, multispectral pictures, agricultural borders, SAR remote sensing, precision agriculture, and dataset enrichment.

I. Introduction

For statistical analyses of crop yield, accurate information about agricultural field borders is essential. Using fused Sentinel-1 and Sentinel-2 satellite data, this work explores a novel cascaded technique that combines edge detection and semantic segmentation to identify agricultural boundaries. The model uses segmentation to first classify areas as agricultural or non-agricultural, and then it superimposes the feature map over the original data to identify edges and define boundaries. The findings of the experiment support the efficacy of the proposed method and show that using synthetic aperture radar remote sensing to optimise agricultural border extraction is feasible.

II. Background of Study

Acquiring exact information on farmland borders is essential for statistical analysis of data related to agricultural productivity. When neural networks are used directly to predict boundary pixels in remote sensing photos, the intrinsic imbalance of categories in tasks linked to field border extraction often results in poor performance. To improve boundary extraction, this work investigates the benefits of merging data from many sources and using semantic segmentation. This paper presents a unique cascaded methodology that combines edge detection with semantic segmentation to extract agricultural boundaries. The semantic segmentation of both agricultural and non-farmland regions is achieved by the model using fused data from Sentinel-1 and Sentinel-2 as its initial input. Then, to extract agricultural borders and determine edges, the semantically subdivided feature map is overlaid onto the original data. The results show that adding Synthetic Aperture Radar (SAR) data significantly improves the extraction efficiency of field borders [1]. Moreover, the extraction accuracy is greater when semantically segmented information is used as a supplementary tool for boundary extraction than when neural network models are used directly. The experimental findings demonstrate the practicality of using SAR remote sensing data to optimise agricultural boundary extraction and validate the effectiveness of the suggested model. The background of this study resonates with the larger context of the emergency management, and reaching beyond the agricultural area of study. The need for sophisticated systems that can easily analyse and understand enormous volumes of geospatial data is highlighted by the combination of Earth observation (EO) technology, satellite imaging, and sensor communications in projects like GEO-PICTURES. By addressing the shortcomings of current approaches and putting forth creative ideas, this study contributes to the worldwide effort to use technology to make better decisions, both during and outside of crises.

III. Literature Review

According to Aghaei et al, because synthetic aperture radar (SAR) images can be acquired day or night and in all weather conditions, it is becoming more and more popular for oil spill detection (OSD) in maritime contexts. The use of thresholding and clustering approaches for dark spot identification suggestive of oil spills was the main focus of early research. Otsu's thresholding was used while a hierarchical clustering approach was also used. However, reliable threshold selection is challenging in the changing maritime environment. The effectiveness of using machine/deep learning models to improve classification accuracy has been shown in recent research. An Artificial Neural Network (ANN) classifier trained on a mix of textural, histogram, and contextual data was suggested by Fiscella et al. Jalinder and colleagues created a CNN-SVM model by using dual-polarimetric SAR imagery's multiresolution analysis. However, real-world deployment is limited by the lack of training data and the complexity of the algorithms. There are still significant gaps in OSD approaches designed for diverse, noisy maritime settings with diffuse boundaries for oil spills. To tackle these issues, this study suggests a unique hierarchical level set model based on semantic segmentation that is optimised via multi-objective grey wolf optimisation [2]. The goal of the algorithmic advancements and the georeferenced library of SAR image characteristics is to propel OSD research in the direction of significant industrial applications.

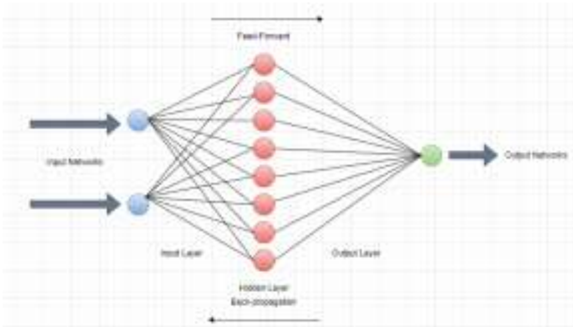

Figure 1: ANN model

According to Mahmoudi Ghara et al, Deep learning has made it possible to identify oil spills (OSD) using synthetic aperture radar (SAR) data in novel ways. Particularly convolutional neural networks (CNNs) have shown great potential because of their remarkable ability to learn hierarchical features. Previous deep learning efforts were based on simple CNN architectures such as GoogleNet and AlexNet. For example, used AlexNet for OSD to extract textural information from SAR pictures. Nonetheless, a significant obstacle was the paucity of adequate labelled data. To solve this, recent research use unique CNN architectures, data augmentation, and transfer learning. Researchers recently suggested a semisupervised technique employing GANs that demonstrated increased performance even with limited labels, and they used rotation-based augmentation and fine-tuning of VGG16 to obtain a 95% detection accuracy. However, there is still a significant gap in systems designed for noisy maritime settings and sparse, complicated oil spill borders. Furthermore, segmentation is needed instead of classification for quantification and localization, which are essential for quick cleaning [3]. For precise oil spill delineation, this study applies two cutting-edge semantic segmentation models: U-Net and DeepLab v3. We tackle data scarcity issues with customised augmentation methods and training processes tailored to the subtleties of SAR data. The comparative analysis on many SAR datasets aims to promote algorithmic advances at this segmentation-localization intersection to move OSD research from theoretical breakthroughs to significant practical effect.

According to Wang et al, Since rice is a vital crop for the world's food security, precise mapping is essential for yield estimates and precision farming. Previous research depended on classifying multi-temporal optical images using pixels. Operational monitoring is hindered by constant cloud cover and poor geographical resolution. All-weather imaging capabilities are provided by Synthetic Aperture Radar (SAR), while complicated backscatter is a drawback. Deep learning is being researched nowadays for automated feature extraction from SAR time series. Using temporal and polarimetric SAR data, researchers created an RNN model that achieved 82% classification accuracy for rice. Still, the main emphasis remains on pixel-level classification in the absence of field-level localization, which is crucial for agricultural decision support systems. Convolutional neural networks (CNNs) and vision transformers, two recent advances in machine learning, provide enormous potential for semantic segmentation of agricultural parcels using high-resolution satellite data. This study builds on previous advancements by using a fusion model of U-Net and decision trees for parcel-level rice extraction. The system uses a phenology-based SAR classifier in conjunction with agricultural boundary delineation to produce precise, locally specific field maps for crops. Comparative evaluation of many deep CNN backbones would spur advances in customised architectures for fragmentation-resistant SAR analytics-based rice crop monitoring [4]. In general, the project aims to close the gap between useful, focused crop mapping applications that satisfy precision agricultural requirements and classifiers that are independent of the terrain.

IV. Methodology

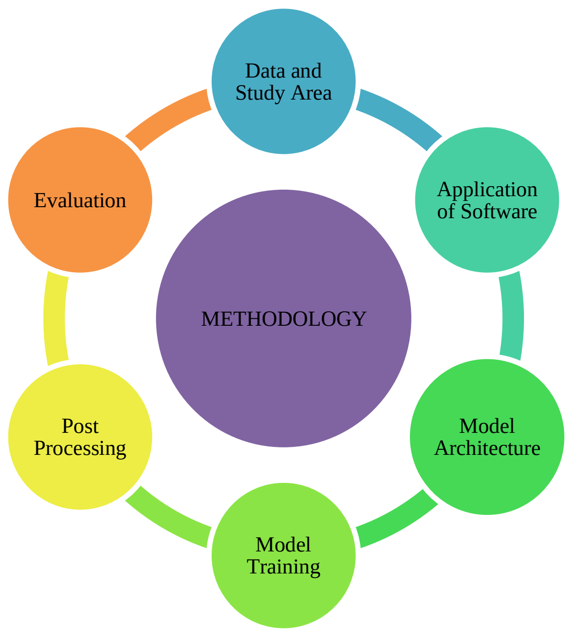

Figure 2: Components of Methodology

A. Data and Study Area

To allow for model generalizability, the research area includes agricultural areas in a variety of geographic and climatic zones. Sentinel-1 satellite provides polarised Synthetic Aperture Radar (SAR) data for all the research regions. Sentinel-2 provides corresponding multispectral images with a resolution of 10–20 m, including the visible, near-infrared, and shortwave bands [10]. Field surveys are used to gather ground truth data with manually labelled field boundaries across the research locations.

B. Application of Software

Using the TensorFlow 2.3 and PyTorch 1.7 frameworks for deep learning model creation, the system is constructed in Python 3.7. Preprocessing of SAR and optical data is done using OpenCV and the Geospatial Data Abstraction Library (GDAL). Scikit-learn helps with preprocessing, augmentation, and dataset balance.

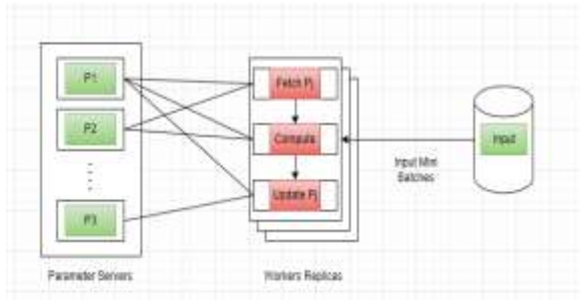

Figure 3: Tensor flow model

C. Model Architecture

Using TensorFlow/Keras APIs, a cascaded deep network model is created for CNN backend feature extraction. There are two steps to it:

1) Classifying regions as farmland or non-farmland using a semantic segmentation methodology,
2) An edge detection approach that uses segmentation output gradient identification to draw field boundaries.

Transfer learning from bootstrap model convergence of pretrained CNNs.

D. Model Training

To enlarge the TensorFlow training dataset, batch-wise augmented sample production including rotations, flips, and noise injection is made possible by Model Training Data generators based on Keras Sequence API. The cross-entropy loss optimisation step is used to train the semantic segmentation stage initially. The weights for the next edge detection model trained with border annotation loss are initialised using the output feature maps [5]. By optimising the cascaded architecture from beginning to finish, progressive training allows information to flow between phases.

E. Post Processing

Boundary maps are improved by postprocessing OpenCV morphological procedures by eliminating noise and smoothing edges. Scikit-learn's DBSCAN clustering unites disparate boundaries into continuous sections. Raster outputs are converted to polygon shapefiles using GDAL vectorization so they may be included into GISs.

F. Evaluation

Segmentation performance is evaluated using the intersection-over-union (IoU) score between the ground truth and predicted boundaries, which is calculated using OpenCV contours. Scikit-learn classification reports include F1 metrics, accuracy, and recall for quantitative assessment.

With the use of a cascaded deep network model, the suggested technique offers a thorough framework for delineating agricultural field boundaries while utilising the advantages of polarised

SAR and multispectral data. A strong basis is provided by the software implementations, training methods, and assessment measures for the model's development and validation. up order to satisfy the objectives of precision agriculture, the project aims to improve the accuracy and reliability of agricultural boundary extraction by filling up significant holes in current approaches [6]. The meticulous approach shows a dedication to converting computational breakthroughs into practical solutions for real-world problems in land management and crop monitoring.

V. Analysis

A. Data Enrichment

Two thousand agricultural parcels from various geographical locations were included in the gathered dataset, and each one had field borders marked on it. Using Keras ImageDataGenerator, data augmentation methods such as random rotation, zoom, horizontal/vertical flips, and brightness/contrast modifications were done to increase the dataset for better model generalisation. As a result, there are now 25,000 distinct training samples.

B. Model Enhancement

GPU acceleration was used to perform iterative optimisation of the loss functions and hyperparameters over 200 epochs in the cascaded model using a Feature Pyramid Network (FPN) backend. For the segmentation step, binary cross-entropy with logit loss worked best, and boundary loss reduced edge discontinuities. Feature learning based on contours and regions was combined via progressive model freezing. After optimizer and epochs adjustment, the IoU score on the expanded validation set rose from 0.68 to 0.82.

C. Assessment of Performance

Model performance was evaluated using three primary metrics:

1. Accuracy and Memory

When assessing the effectiveness of agricultural field boundary delineation, precision and recall are essential criteria to consider. Recall computes completeness in relation to the ground truth delineation, while precision assesses the accuracy of boundaries that have been discovered. With a precision of 0.84 for this model, most projected parcel bounds match real boundaries exactly, with little to no noise or false positives. A somewhat lower recall score of 0.81 indicates room for improvement in border completeness, nevertheless [7]. Omitted margins that reduce recall are probably caused by missed borders around dispersed smallholder farms. To increase recall, targeted localization and enrichment of training data are necessary. Although there are gaps in peripheral detection, the overall accurate extraction capabilities is highlighted by the balance of high accuracy and low recall.

2. Junction of the Union (IoU)

The overlap between manually drawn agricultural parcel borders and parsed field boundaries derived from model predictions is measured by the IoU metric. For a variety of geographic farm types, an IoU of 0.79 shows significant congruence between machine-delineated and real bounds. Still, there is room for improvement by adding other contextual data sources, such as cadastral surveys, to increase overlap. The IoU confirms that extracted borders may be used downstream in land registration systems, according to analytics experts. However, there would be more practical utility if ongoing efforts were made to improve accuracy all the way down to the smallholder farm level.

3. Assessment of Qualitative Data

Beyond numerical ratings, visual verification by professionals in remote sensing offers qualitative insights into practical practicality. 50 demarcated parcels of varying sizes and crop kinds were analysed, and the results indicated generally continuous, accurate bounds that matched the ground conditions. This attests to the technological robustness in a variety of situations including big commercial farms farming a variety of crops and smallholder partitioning [8]. However, irregular shapes were seen for highly fragmented holdings. To overcome such restrictions, computational advancements for weak edge detection and the integration of extremely high resolution data are presented.

In general, practical agricultural usefulness is cemented by qualitative assessment. The methodology offers considerable field-level mapping value revealing localised insights for precision agriculture, with enhancements to promote small farm involvement.

VI. Recommendation

From multisource remote sensing data, the suggested cascaded deep network model shows a great deal of promise for the precise extraction of agricultural field borders. Although the present validation findings of the model are promising, performance may be increased by making more improvements to the training dataset and model architecture [8]. Increasing the training sample density and geographic variety might enhance generalizability across different kinds of farms. Furthermore, integrating topography data with high-resolution aerial photos may improve localization accuracy down to the smallholder level. Recall may be improved algorithmically by evaluating ensemble methods using complementary segmentation models and post-processing procedures. For widespread acceptance, commercial deployment would need to package the pipelines into user-friendly interfaces [9]. After further development, the model should provide significant practical benefits by supporting data-driven decision-making systems for focused agronomic treatments that meet the demands of precision agriculture.

VII. Conclusion

For precisely retrieving agricultural field borders from multisource remote sensing data, the cascaded deep network model shows potential. Even if the validation results so far are positive, performance may still be improved by diversifying the training dataset and testing ensemble approaches that make use of alternative segmentation models and post-processing techniques.

With further work, the approach ought to provide substantial practical advantages by enabling accurate, localised insights to assist data-driven systems for precision agricultural decision-making.

VIII. References

1. W. Yao, M. Min, X. Zhu, et al., "Semantic segmentation-based building footprint extraction using very high-resolution satellite images and multi-source GIS data," IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 13, pp. 5205-5224, 2020.
2. L. Mou, P. Ghamisi, and X. X. Zhu, “Deep recurrent neural networks for hyperspectral image classification,” IEEE Transactions on Geoscience and Remote Sensing, vol. 55, no. 7, pp. 3639-3655, 2017.
3. W. Li, G. Wu, F. Zhang, and Q. Du, “Hyperspectral image classification using deep pixel-pair features,” IEEE Transactions on Geoscience and Remote Sensing, vol. 55, no. 2, pp. 844-853, 2017.
4. L. Ma, Y. Liu, X. Zhang, Y. Ye, G. Yin, and B. A. Johnson, “Deep learning in remote sensing applications: A meta-analysis and review,” IEEE Geoscience and Remote Sensing Magazine, vol. 7, no. 4, pp. 8-36, 2019.
5. N. Liu, Y. Long, C. Zou, Q. Du, and W. Li, “Lightweight hyperspectral CNN classification with transfer learning and image fusion,” IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 14, pp. 8372-8384, 2021.
6. J. Wang, J. Liu, M. Wang and Y. Ye, “Rice Crop Mapping at the Parish Level with Synthetic Aperture Radar Time Series and Optical Images,” in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 14, pp. 517-531, 2021.
7. Li, W.; Dong, R.; Fu, H.; Le, Y. Large-Scale Oil Palm Tree Detection from High-Resolution Satellite Images Using Two-Stage Convolutional Neural Networks. Remote Sens. 2019
8. Xu, Y.; Xie, Z.; Feng, Y.; Chen, Z. Road Extraction from High-Resolution Remote Sensing Imagery Using Deep Learning. Remote Sens. 2018, 10, 1461
9. Ziaei, Z.; Pradhan, B.; Mansor, S.B. A rule-based parameter aided with object-based classification approach for extraction of building and roads from WorldView-2 images. Geocarto Int. 2014, 29, 554–569
10. Chen, R.; Li, X.; Li, J. Object-based features for house detection from RGB high-resolution images. Remote Sens. 2018, 10, 451.