DEEP LEARNING WITH SYNTHETIC APERTURE RADAR: CROP CLASSIFICATION

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Background:

Synthetic Aperture Radar (SAR) is a remote sensing technology that employs a moving antenna to capture radar snapshots of a target area. The antenna transmits and receives signals as it traverses the region of interest, collecting data from various positions. SAR's unique ability to penetrate clouds and operate in darkness allows it to gather valuable information in challenging weather conditions. The raw SAR data undergoes specialized processing to generate high resolution images.

Objective:

Design a Convolutional Neural Network (CNN) with improved computational efficiency. We aim for an architectural complexity of O(n log n) compared to the typical complexity of $O(n^2)$ of standard CNNs. Our proposed approach aims to handle these large, memory-intensive SAR datasets more efficiently, potentially enabling faster processing and analysis of high-resolution SAR imagery.

Methods & Resources:

- SAR Imagery Crop Classification Dataset[2]
- Python, Jupyter Notebook
- Histogram Equalization
- Noise Speckling
- Continuous Wavelet Transform[3]
- Discrete Wavelet Transform
- Convolutional Neural Network

[1]

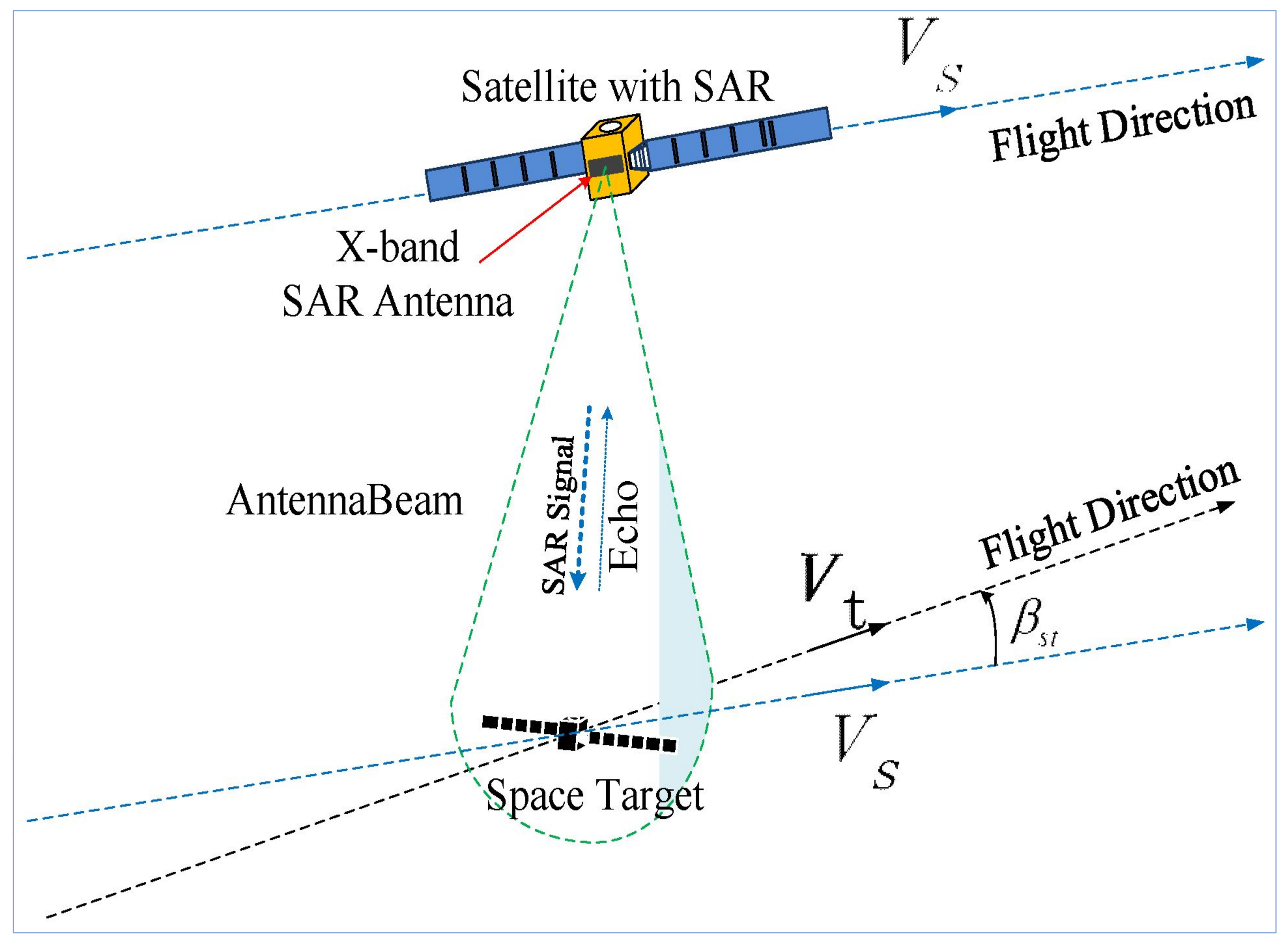

Figure 1: Visualization of SAR Process

Figure 2: SAR Image of target region in Western Cape, South Africa

- Extracted 2,435 patches from SAR image of 128x128x1
- Labeled patches based on geographic coordinates
- Labels consists of 5 crop classes: Barley, Canola, Lucerne, Small Grain, Wheat
- 80% of data used for training, 10% for validation, 10% for testing

Conv2D Block:

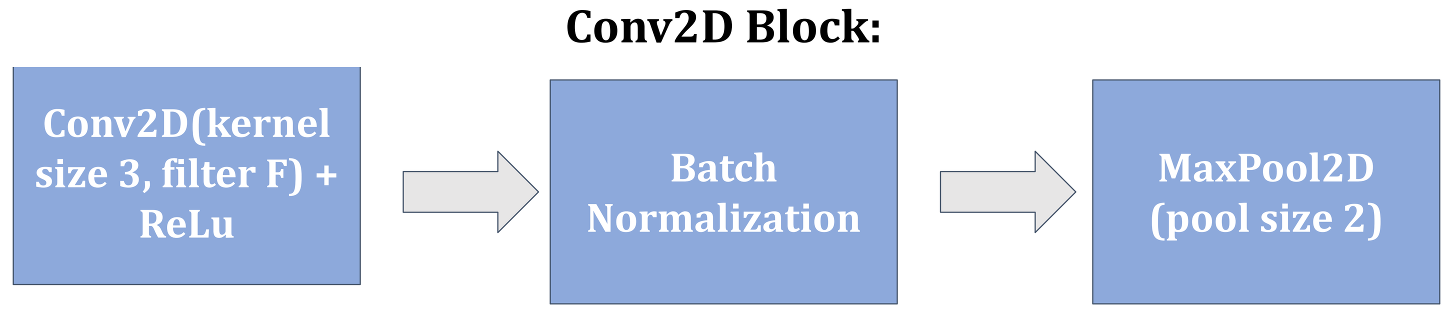

Figure 3: Contents of Convolution Layer Block in figure 4

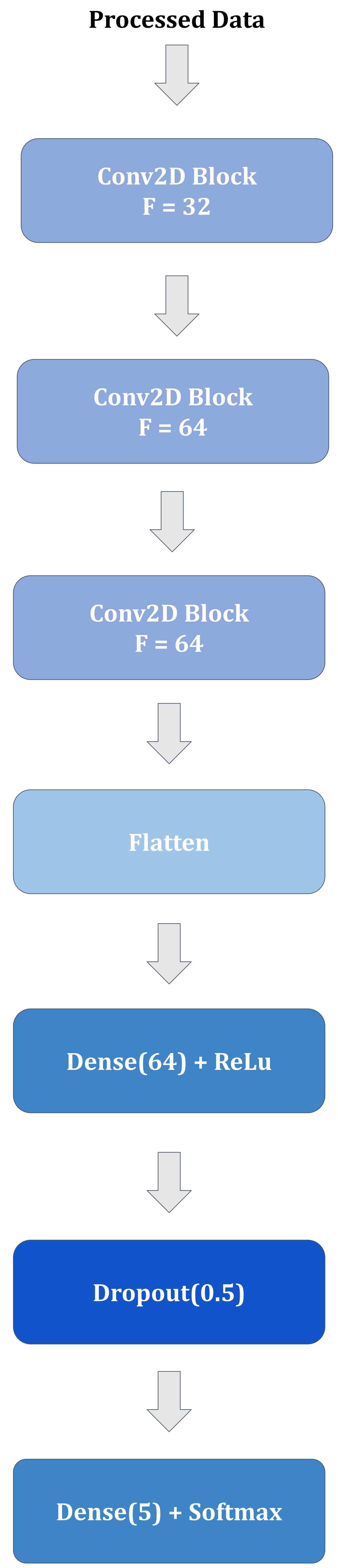

Figure 4: Flowchart of CNN Architecture

Results:

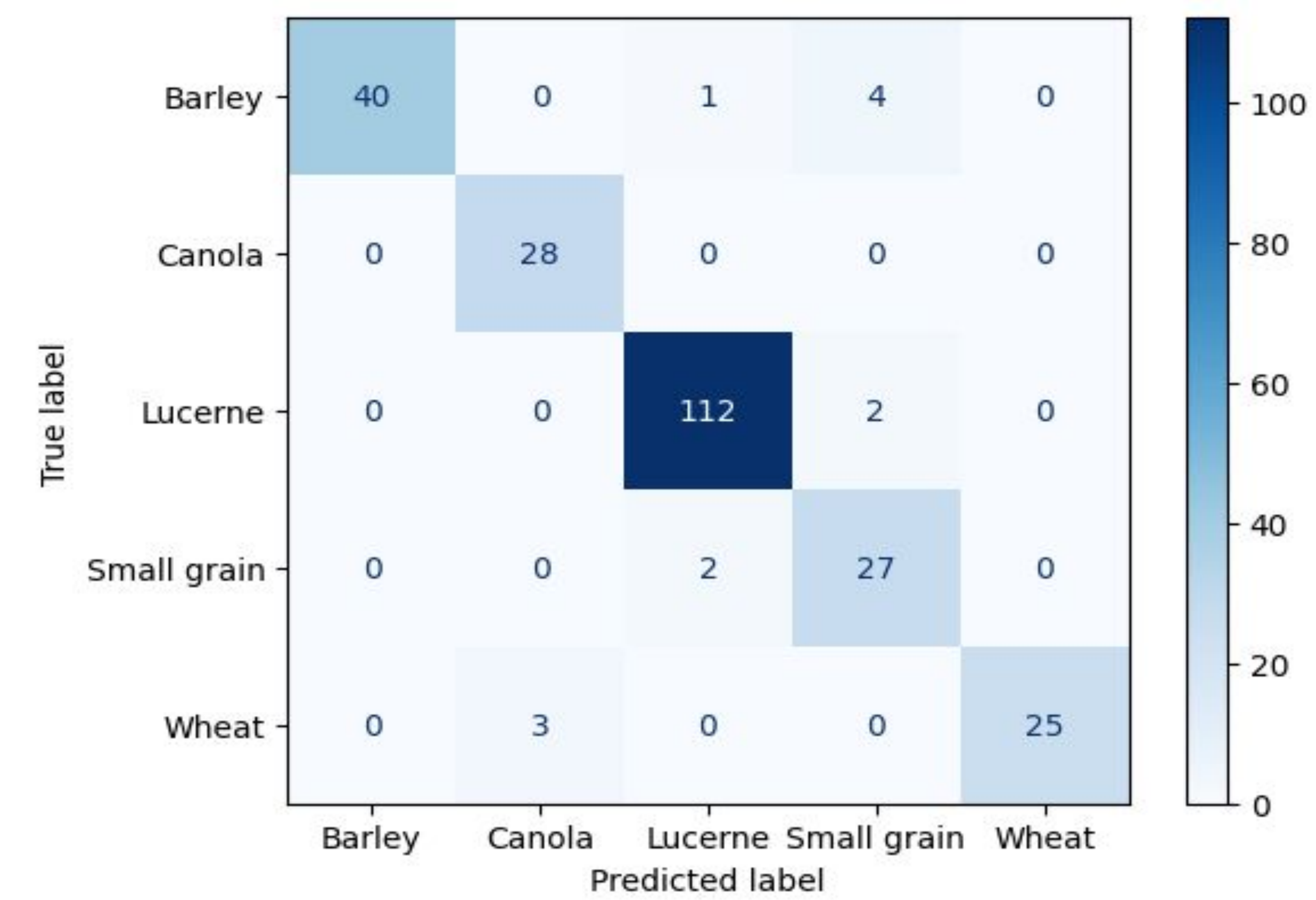

Figure 5: Confusion Matrix displaying ground truth vs predicted labels

With Continuous Wavelet Transform:

- Reached accuracy of 93.85% on test dataset
- CWT is computationally costly

With Discrete Wavelet Transform:

- Reached accuracy of 94.26% on test dataset
- Better computational efficiency
- Can further improve accuracy with hypertuning

Neural Network Architecture Analysis:

- Maintained desired accuracy while reducing to 3 convolution layers
- <3 convolution layers significantly decreases accuracy

Future Works:

- Continue research on computing & reducing complexity of the CNN architecture with radar inputs
- Experiment with larger & raw datasets

References:

[1]https://www.mdpi.com/applsci/applsci-12-04848/article_deploy/html/images/applsci-12-04848-g001.png
[2]A Fusion Dataset for Crop Type Classification in Western Cape, South Africa
[3] arXiv:2309.12094

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