Deep Learning based Paddy Land Abandonment Detection Using Multitemporal Polarimetric SAR Patterns

Authors: Shivam Kasture, Aishwarya Hegde A & Pruthviraj Umesh



Abandoned paddy land

Introduction

Paddy land abandonment is rising in Udupi, Karnataka, India due to labour shortages, high costs and wildlife conflict. This threatens food security and disrupts traditional irrigation systems.
Optical remote sensing struggles in Udupi's cloudy monsoon season. Sentinel-1 Synthetic Aperture Radar (SAR) overcomes this with consistent imaging. This study uses backscatter and polarimetric parameters from Sentinel-1 SLC data, combined with deep learning, to detect abandonment patterns from 2021 to 2024 during the main paddy season.

Objective

To develop and compare deep learning models using parameters derived from multitemporal Sentinel-1 SAR data for accurate detection of paddy land abandonment in Udupi district between 2021 and 2024.

SAR Preprocessing

The Sentinel 1 SLC data was preprocessed on SNAP. The workflow is as follows:

For backscattering coefficients (σ^0VV, σ^0VH):
Split → Apply Orbit File → Calibration → Deburst → Multilooking → Speckle Filtering → Range Doppler Terrain Correction → Convert to dB.

For polarimetric parameters (Entropy, Anisotropy, Alpha Angle):
Split → Apply Orbit File → Calibration → Deburst → Multilooking → Polarimetric Matrix Generation → Polarimetric Speckle Filtering → Range Doppler Terrain Correction → Polarimetric Decomposition (H/A/α)

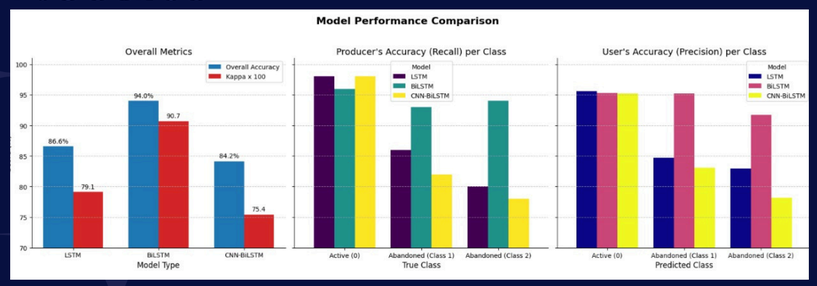
Temporal values for all five parameters were extracted per pixel for ground truth data (comprising of active & abandoned classes) and compiled as time series for deep learning input.

Deep Learning Models

The ground truth data has classes: Active & Abandoned (Class 1: Cultivated till 2021 & never after that, Class 2: Cultivated till 2022 & never after that).
Three DL models were tested on ground truth data using time series of the five features: σ^0VV, σ^0VH, Entropy, Anisotropy & Alpha Angle.

LSTM: A two-layer LSTM network captured temporal dynamics in the input features with dropout and batch normalization applied for regularization.
BiLSTM: Two stacked Bidirectional LSTM layers captured temporal patterns. Regularization was applied using BatchNorm and Dropout. Final classification used a softmax layer.
CNN-BiLSTM: Time-distributed Conv1D layers extracted intra-year patterns before passing sequences to BiLSTM layers for temporal learning.
Training: Adam optimizer, EarlyStopping and learning rate scheduling were applied for robust training.

Results



Conclusion

Among the three models tested, the BiLSTM achieved the highest performance with very high overall accuracy of 94% and a Kappa score of 0.907. It outperformed both LSTM and CNN-BiLSTM (with high accuracies of their own) in terms of recall and precision across all classes, particularly in identifying abandoned paddy fields.
This study demonstrates the effectiveness of deep learning, particularly BiLSTM, in detecting paddy land abandonment using multitemporal SAR and polarimetric features. The high classification accuracy supports its applicability for large-scale agricultural monitoring in cloud-prone, monsoon regions. Such methods can aid policymakers in timely intervention, promoting sustainable land use and food security.