Convolution Neural Networks Based Crop Type Classification using Spatio-Temporal Remote Sensing Data

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Abstract
Deep learning-based algorithms are increasingly prevailing over traditional pixel-based methods for image classification, as the growing adoption of these technologies drives superior performance. Deep learning and multi-temporal images work well together to produce better precision of crop type distribution. The current study incorporates different sensors of varying spatial and spectral resolution, belonging to monthly/fortnightly time series (2021-2022) to classify various crop types in part of Ranchi district, which has diverse economic crops mainly rice, wheat, mustard, peas, maize, ragi, and vegetable crops. The study utilized time-series datasets which are constructed based on vegetation indices (VIs) and spectral stacking, respectively, using three-dimensional-convolution neural networks (3D-CNNs) and random forest-based algorithms. The results obtained from three-dimensional Convolution neural networks outperform the accuracy gained from random forest. It shows that 3D convolution neural networks give 96.77% accuracy using a monthly stack of Normalized Difference Vegetation Index (NDVI) of Sentinel-2 datasets while the random forest algorithm gives an overall accuracy of 94.52% with a kappa coefficient 0.93. The present study shows that the 3D-CNNs-based deep learning framework provides an effective and efficient method of time series representation in multi-temporal classification tasks.

Keywords Crop mapping**,** Deep Learning, Convolution Neural Networks, 3D-CNNs, Random Forest

Introduction

Accurate crop type classification is essential for informed decision-making in precision agriculture, resource allocation, and land-use planning (Cai et al., 2018; Conrad et al., 2014). Traditional methods of crop identification often rely on manual interpretation of satellite imagery or limited spectral indices, which may lack the capacity to capture the complexity of agricultural landscapes (Pantazi et al., 2016).

In recent years, the integration of advanced technologies in agriculture has become imperative to address the challenges of food security, resource optimization, and sustainable land management(Massey et al., 2017). Remote sensing, with its capacity to capture detailed information about the Earth's surface, has proven instrumental in providing critical insights for agricultural monitoring(Lin et al., 2022). In particular, the advent of high-resolution, multispectral satellite missions such as Sentinel-2 has opened new frontiers for extracting spatio-temporal patterns in crop dynamics. Deep learning has proven effective in various machine-learning tasks, with Convolutional Neural Networks (CNNs) emerging as a prominent architecture for remote sensing applications. The increasing use of CNNs in diverse remote sensing problems and satellite data types underscores their effectiveness in tasks like land cover classification, semantic segmentation, and object detection. Notably, Two-Dimensional Convolutional Neural Networks (2D-CNNs) focus on spatial-spectral information, while Three-Dimensional Convolutional Neural Networks (3D-CNNs) leverage time series data in multi-spectral and hyperspectral domains, as evidenced by numerous publications (Gallo et al., 2023; Ji et al., 2018; Varela et al., 2022).

By harnessing the power of 3D-CNNs, which excel in learning hierarchical features from large and diverse datasets, this research aims to provide a robust solution for automated and accurate crop type classification (Ge et al., 2021; Joshi et al., 2023; Khan et al., 2023; van Klompenburg et al., 2020; Xu et al., 2020; Yi et al., 2022; Zhong et al., 2019). This study focuses on the application of 3D-CNNs for crop type classification, leveraging the rich information embedded in spatio-temporal remote sensing data (Wang et al., 2021). CNNs have demonstrated remarkable success in image classification tasks, and their application to crop type classification stands as a promising avenue to enhance the precision and efficiency of agricultural monitoring systems (Xu et al., 2021; Yan & Ryu, 2021).

Previous studies have explored various machine learning techniques(Gao et al., 2021) for crop classification, ranging from traditional classifiers to more advanced methods such as Support Vector Machines (SVMs) and Random Forests (RF) (Asgari & Hasanlou, 2023; Khan et al., 2023). However, the inherent spatial and temporal dynamics of agricultural landscapes require models capable of understanding both local and global contextual information. CNNs have proven effective in addressing this need, showcasing superior performance in image recognition tasks and paving the way for their application in the field of precision agriculture (Ajadi et al., 2021).

Several noteworthy studies have successfully employed CNNs for crop type classification using remote sensing data. For instance, (Zhong et al., 2019) demonstrated the utility of CNNs in discriminating between crop types with high accuracy, while Jones et al., (2020) explored the integration of temporal information to enhance the classification performance over multiple growing seasons.

This study aims to contribute to the existing body of knowledge by presenting a comprehensive investigation into the application of 3D-CNNs and RF model for crop type classification using spatio-temporal remote sensing data in parts of Ranchi district, Jharkhand. Through the utilization of Sentinel-2 datasets and innovative neural network architectures, we seek to achieve a higher level of accuracy and generalization in crop type identification, thereby facilitating more effective agricultural management practices.

Materials and Methods

Study Area:

Study area consists of Ratu block which is located on the Ranchi plateau proper, lies between 23.41° N latitude and 85.2° E longitude (Figure 1). It has total geographical area of 127.27 Km^2 and an average elevation of 650 m above mean sea level. The study area has a subtropical climate with hot summers from March to May and consistent rainfall during the southwest monsoon from June to October. The winter season, spanning November to

February, is characterized by dry and cold weather. Normal annual rainfall averages 1394mm. The land is undulating containing 97.62% of the total area as cultivable, out of which 34.19% is irrigated land (in 2011). The major crops grown in this region are rice, wheat, ragi, mustard, maize and vegetables crops.

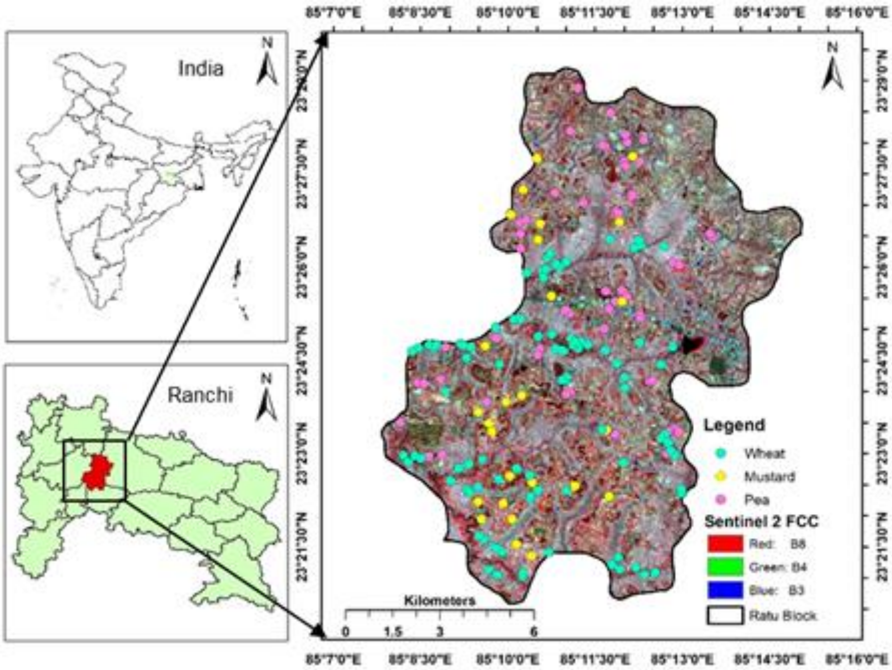

Fig. 1 Location map of the study area shows RGB (R:B8,G:B4,B:B3) composite of sentinel-2 data (dated: March 2022).

Datasets:

*S*entinel-2 data

Present study utilized time-series datasets of Sentinel-2 data for crop type mapping for Rabi season in Google Earth Engine (GEE) platform. This data offers distinct advantages in crop type mapping, making it a valuable resource for precision agriculture. With its high spatial resolution of 10 meters and multi-spectral capabilities, Sentinel-2 provides detailed and comprehensive imagery essential for discriminating between various crop types. The mission's revisit frequency allows for frequent and consistent monitoring, capturing temporal changes in crop growth and enabling the identification of seasonal variations. Additionally, Sentinel-2's wide spectral range, including infrared bands, enhances its capacity to assess vegetation health, detect anomalies, and differentiate between different crops. The open and free access to Sentinel-2 data further promotes accessibility for researchers, farmers, and decision-makers, fostering advancements in crop monitoring and land management practices.

Sample Data:

Data sampling took place on three distinct dates: January 13th, February 10th, and March 13th, 2022. A comprehensive total of 300 crop type samples were meticulously collected, with a specific focus on various crop varieties. This collection comprised 100 samples for wheat, 50 for mustard, 60 for peas, and 90 for vegetable crops. The thorough sampling across different dates and diverse crop types ensures a representative dataset for subsequent analysis and assessment.

Methodology:

The methodological workflow consists of following steps: 1) data pre-processing to create cloud free monthly mosaic datasets for the study area, 2) generation of NDVI time series, 3) generation of training and validation samples, 4) data classification using RF and 3D-CNNs, 4) Accuracy assessment and validation (Figure 2).

Data pre-processing

Present study used Sentinel-2 time series data for crop type classification for rabi crop (December 2021-April2022) in google earth engine (GEE) platform. The data pre-processing includes generation of cloud free, monthly mosaic datasets for study area. Cloud pixel percentage was taken less than 2% (using filter function in GEE), which provides precise information of data.

Generation of NDVI time-series

Monthly time-series NDVI was generated from 10m resolution red and near-infrared spectral bands (Equation (1)) to study the temporal growth patterns of the various cropland classes.

$$NDVI = \frac{NIR-RED}{2\mathrm{NIR}+\mathrm{RED}} \quad \text{Eq. (1)}$$

It is one of the most used vegetation indices for temporal vegetation studies as it minimizes the spectral noise effects caused by topographic variations and illumination conditions (Belgiu & Csillik, 2018). Other vegetation indices or spectral bands were not considered in the present study.

Generation of training and validation samples:

For the current study, a total of 300 crop type samples were collected. Of this dataset, 70% was utilized for training the model, while the remaining 30% was reserved for validation purposes.

Random Forest algorithm:

Random forest (RF) is a non-parametric, well-documented and mature classification method for satellite-based imagery (Adrian et al., 2021). This ensemble method involves creating of numerous decision trees during training. The number of trees serves as input parameter, and for each tree, a random subset of variable is selected to construct a single tree. (Bhuyan et al., 2023; Cao et al., 2021; Gao et al., 2021; La Rosa et al., 2019). However, a greater number of decision trees doesn't always allow to improved classification accuracy (Prins & Van Niekerk, 2020).

In this study, RF model was used for time-series stack of normalized vegetation difference index (NDVI) computed from sentinel-2 data within the study period December2021 through April 2022. This model was run in google earth engine platform that allows a max pixel sample of 5000 and maximum number of 500 trees. The total number of samples used in this study was 300 and 100 number of trees. Research indicates that the optimal number of decision trees falls within the range 100-500 (Adrian et al., 2021; Belgiu & Csillik, 2018; Bhuyan et al., 2023).

3D-CNNs algorithm:

Three-Dimensional Convolutional Neural Networks (3D-CNNs) stand as a powerful tool in deep learning, extending the capabilities of traditional CNNs to capture intricate spatio-temporal patterns (Zhong et al., 2019). It consists of multiple layers and are mainly used for volumetric image processing such as time-series datasets. The process of a 3D-CNNs encompasses various essential stages for the handling and examination of time series data. It includes several steps such as; data preprocessing, architecture design, convolution layer, pooling or subsampling layer, fully connected layers, back propagation and training, evaluation and validation, and testing.

This study utilized rectified linear unit (ReLU) and softmax activation function for dense and output layer. In combination, ReLU and softmax contribute to the effectiveness of neural networks for crop type mapping. ReLU promotes efficient training through non-linearity, while softmax ensures meaningful and calibrated predictions, enhancing the overall accuracy and interpretability of the crop classification model.

Accuracy assessment:

The accuracies of the pixel obtained from RF classifier and 3D-CNNs algorithm were evaluated in terms of overall accuracy, producer's accuracy, user's accuracy and kappa coefficient.

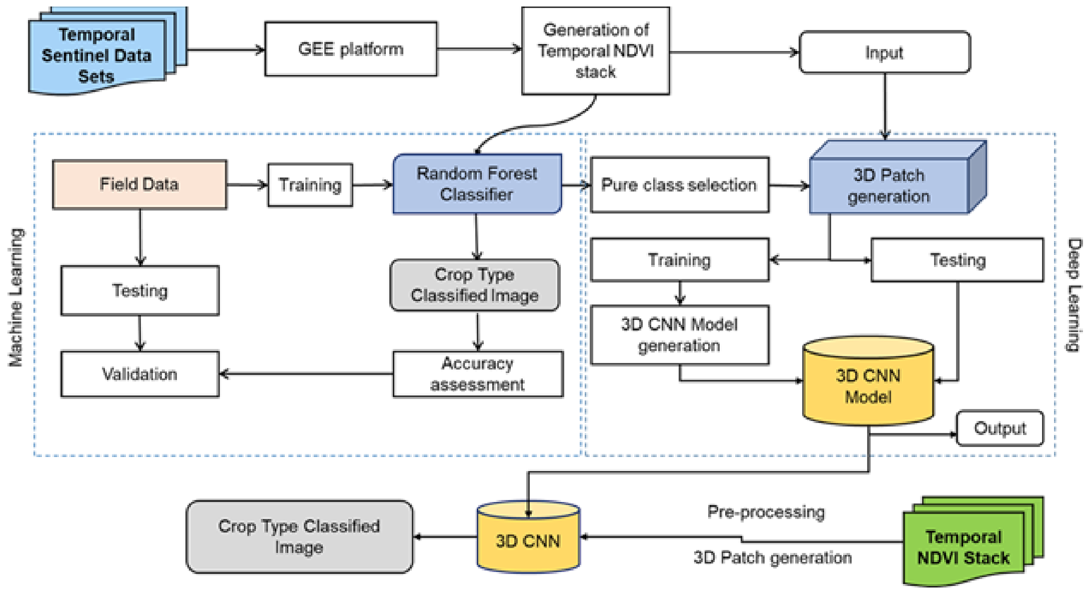

Fig. 2 Methodological flowchart adopted for crop type mapping in the study area.

Results & Discussions

Analysis of Classification using multi-temporal algorithm:

RF classification:

Random forest classifier has demonstrated the strength of detection of multiple crops in this district for rabi season (Figure 4), which corresponds to four rabi season crops viz., wheat, mustard, pea, and vegetables. The overall accuracy and kappa coefficient was obtained as 94.52% and 0.93 (Table 1) indicating the response of multi-date rabi season spectral response in Visible Near Infrared Red (VNIR) region to the algorithm, that takes care of hierarchical elimination or aggregation of decision rules.

3D-CNNs classification:

The classification using a 3D Convolutional Neural Network (3D-CNNs) achieved an impressive overall accuracy of 96.77%, coupled with a robust kappa coefficient of 0.95 (Table 1). This classification was based on the utilization of the Normalized Difference Vegetation Index (NDVI) stack derived from Sentinel-2 data.

Within the region of interest, the total area identified as part of the Rabi cropping season was found to be 11.83 Km^2 (Figure 5). Among these, specific crop types were discerned, revealing areas of 5.96 Km^2 for wheat, 1.66 Km^2 for mustard, 1.97 Km^2 for peas, and 2.25 Km^2 for vegetable cultivation. Moreover, the classification process identified other non-cropped areas, encompassing 59.72 Km^2, indicating regions without active agricultural cultivation. Additionally, areas designated as rice fallow were also recognized, totalling 55.71 Km^2. These results underscore the efficacy of the 3D-CNNs in accurately delineating different crop types within the specified area, showcasing its potential for high-precision crop type classification in the context of agricultural monitoring using Sentinel-2 data.

Comparison with the state of art classifier: 3D-CNNs have been shown to achieve state-of-the-art results on crop type mapping tasks. The 3D CNNs achieved an overall accuracy of 96.77%, which is significantly higher than the accuracy of traditional machine learning algorithms such as random forest. The overall results shows that the 3D-CNNs approach is more robust for cropland classification than any other pre-existing deep learning models. Moreover, hyper tuning of parameters is required to adapt to new problem. The limitation of proposed model is the availability of remote sensing datasets and requirement of high computing power for larger area of interest. Future work should focus on implementation of 3D-CNNs using a greater number of bands including various vegetation indices. Furthermore, it can be also tested using hybrid fusion datasets.

Table 1 Accuracies and Kappa coefficients.

Method	Overall Accuracy	Kappa Coefficient
Random Forest	94.52%	0.93
3D-CNNs	96.77%	0.95

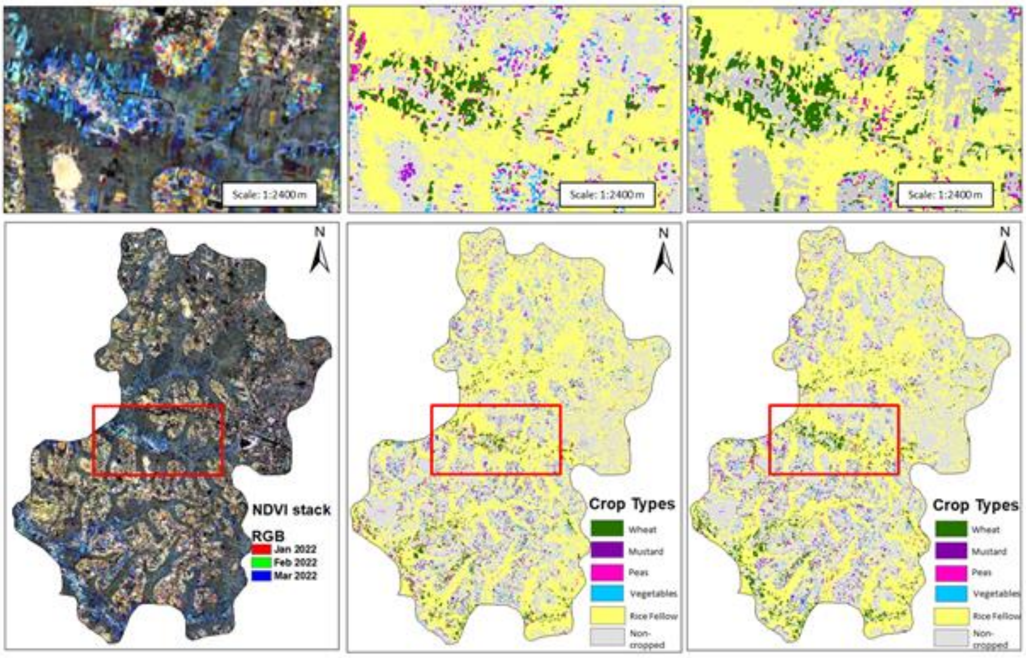

Fig 4 Rabi cropped type classification map: (**a**) NDVI composite: Red- January 2022; Green- February 2022; Blue- March 2022 (**b**) Classified using RF classifier. (c) Classified using 3D-CNNs

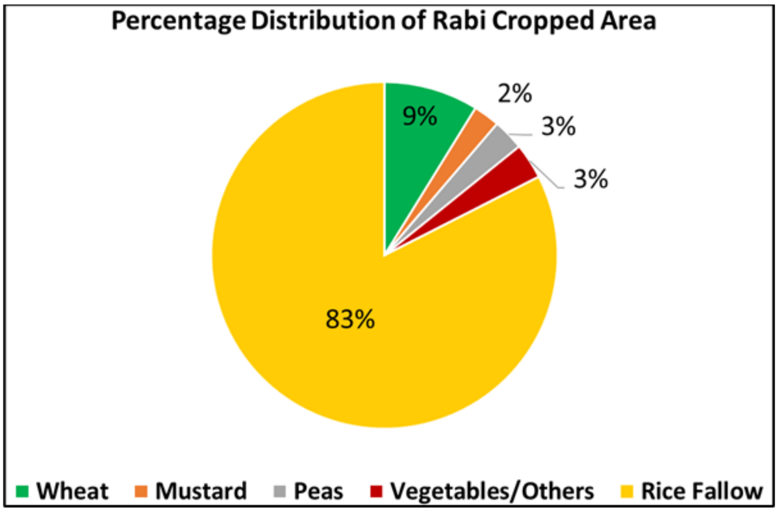

Fig. 5 Distribution of cropped type for Rabi season (2022) classified using 3D-CNNs

Conclusions

In this paper, we proposed a 3D-CNNs and RF model for crop type mapping. 3D-CNNs, in contrast to traditional deep learning models reliant on local labeled samples, addresses label missing issues by acquiring knowledge from labeled samples in diverse domains and dynamically transferring this knowledge to target domains. The choice between Random Forest and 3D-CNNs for crop type mapping hinges on the specific characteristics of the data and the task at hand. Random Forest, with its ensemble learning and non-linear modeling capabilities, is a reliable choice for tasks where interpretability and feature importance are critical. On the other hand, 3D-CNNs shine in tasks requiring end-to-end learning and a deep understanding of spatio-temporal patterns in the data. The decision should be guided by the nature of the data, the availability of computational resources, and the specific requirements of the crop type mapping application. Combining the strengths of both techniques may also be explored for enhanced accuracy and interpretability.

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