Performance Analysis of Deep Learning Classification for Agriculture Applications Using Sentinel-2 Data

Gurwinder Singh[1](✉), Ganesh Kumar Sethi[2], and Sartajvir Singh[3]

[1] Punjabi University, Patiala 147 002, Punjab, India
[2] Multani Mal Modi College, Patiala 147 001, Punjab, India
[3] Chitkara University School of Engineering and Technology, Chitkara University, Solan 174 103, Himachal Pradesh, India
sartajvir.singh@chitkarauniversity.edu.in

Abstract. North Indian states are largely covered with agricultural land which plays an important role in nation's economy development. Remote sensing offers a cost-effective and efficient solution for sustainable monitoring and mapping of agricultural land. In past, various classification algorithms were developed and implemented for agriculture applications. But the conventional techniques are generally based on machine learning algorithms which are easy to implement but at the same time require human intervention on decision making. Nowadays, deep learning algorithms are becoming more popular due to the presence of trained models and one-time processing. However, the deep learning model required a large amount of computation time and needs to be tested in different regions for different applications. In the present work, the deep learning algorithm has been tested over agricultural land (over a part of Punjab state, India) using Sentinel-2 imagery. The major classes considered in the present analysis are vegetation area, water, and buildup area. For validation purposes, output classified maps are compared with reference datasets which were acquired from field observations for some points. The statistical results have shown that more than 80% of accuracy has been obtained using a deep learning algorithm. This study has many applications in the monitoring and mapping of land use land cover regions using a deep learning algorithm.

Keywords: Sentinel-2 · Deep learning · Agriculture mapping · Classification · Remote sensing

1 Introduction

Agriculture land is the backbone of the Indian economy and the major source of national income via agriculture and allied activities. Agriculture is acting as a supply chain of food products and raw material for industrial development, commercial activities, and international trade [1]. It has also been observed that in India, agriculture activities have been continuously decreased due to urbanization or the growth of other sectors [2].

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But still as compared to other countries the rate is high [3]. It is more important to perform a comprehensive assessment of agriculture concerning crop production which is essential to meet the demands of the food supply chain [4]. For mapping and validating the agricultural land, field observation methods are generally followed which are time-consuming, expensive, and tedious tasks and also sometimes not feasible for inaccessible areas [5].

For large land-use and land-cover mapping and monitoring, remote sensing plays an important role at a lower cost. Remote Sensing (RS) dataset can be broadly categorized into two types first is optical sensor and another is microwave [6]. The optical remote sensing dataset is further classified such as Landsat-8 [7], Sentinel-2 [8], MODIS (Moderate Resolution Imaging Spectroradiometer) [9], AVIS (Avian Information System) the classification requires the training data to classify the input data such as DL (Deep Learning), ANN (Artificial Neural Network), CNN (Convolutional Neural Network). The microwave remote sensing dataset is also classified such as SAR (Synthetic Aperture Radar), SCATSAT-1 (Scatterometer Satellite-1) [10] represents the classified dataset obtained from two different classifier LMM (Linear Mixer Model) and ANN (Artificial Neural Network), respectably. In past, various techniques have been developed and modified to improve the utilization of remotely sensed data [11]. However, most of the traditional techniques or models are generally based on machine learning algorithms and proven as significant in large area mapping [12]. But such methods are generally based on either supervised or unsupervised models [13]. From the literature [14], it has been seen that unsupervised methods are not able to extract the actual information satellite imagery due to dependency on untrained data [15]. On the other hand, supervised methods provide better results but are limited by the requirement of training data which varies from person to person [16].

In literature, various datasets have been explored such as Sentinel 1 dataset for agriculture land mapping [17], a high-resolution satellite dataset to classify the cloud, shadow, and land cover [18] as shown in Table 1. Moreover, [19] investigated the suitability and potential of DCNN in the supervised classification of POLSAR (Polarimetric Synthetic Aperture Radar) dataset. Spatial information was naturally employed in terrain classification due to the properties of convolutional networks. The deep learning algorithms take the advantage of the trained model to reduce the intervention of the user's skill. However, the deep learning model requires more computation power and time and needs to be tested in different regions for different applications [20].

The main aim of this research paper is to estimate and validate agriculture using a deep learning algorithm over a part of Punjab state, India using the Sentinel-2 dataset. In the study area, the major classes are vegetation area, water, and buildup area [23]. Previously the classification of the agriculture land is done to the door-to-door survey. Here in the proposed work remote sensing dataset is being used for automatic classification of agriculture land. The introduction is followed by the study site and the associated dataset in Sect. 2; Sect. 3 describes the methodology of the deep learning algorithm with the Tensor Flow model for agriculture land cover classification using the sentinel-2 dataset. The experimental results are discussed in Sect. 4. At last, the conclusion has been drawn in Sect. 5.

Table 1. Some papers on agricultural land, the number of classes, and classification accuracy.

Author	Species	Accuracy	Dataset	Approach
[18]	11	96%	Sentinel-1	RNN[a], K-NN[b], RF[c] and VSM[d]
[21]	22	86.2%	Colour Plant Images	DCNN[f]
[22]	10	77%	WV-2[e]	ANN[g]
[23]	5	87.3%	Landsat-8 OLI/Sentinel-2 MSI	ML[h]
[24]	11	85%	Sentinel-1	CNN[i]
[25]	14	92%	Sentinel-2	ML[h] and DL[j]
[26]	8	94.94%	Sentinel-1/Sentinel-2	TWINNS[k]
[27]	4	94.85%	Landsat-8/Sentinel-2	FCNs[l]
[28]	15	96.5%	Sentinel-2	R-CNN[m]
[29]	10	98.7%	Sentinel-2	CNN[i] and R-CNN[m]
[30]	3	97.53%	Digital images	R-CNN[m]
[31]	2	91%	Landsat-8/Sentinel-2	DL[j]
[32]	55	85%	NS-55	DLCD[n]

[a]RNN: Recurrent Neural Network, [b]K-NN: K-Nearest Neighbors, [c]RF: Random Forest, [d]VSM: Vector Support Machines, [e]DCNN: Deep Convolutional Neural Networks, [f]WV-2: World View-2, [g]ANN: Artificial Neural Network, [h]ML: Machine Learning, [i]CNN: Convolutional Neural Network, [j]DL: Deep Learning, [k]TWINS: TWIn Neural Network for Sentinel Dataset, [l]FCNs: Fully Convolutional Networks, [m]R-CNN: Recurrent-Convolutional Neural Network, [n]DLCD: Deep Learning Change Detection

2 Study Area and Satellite Dataset

The study site lies in district Fatehgarh Sahib and Patiala, Punjab, having geographic coordinates between 30°26’N–30°33’N in latitude and 76°21’E–76°29’E in longitude as shown in Fig. 1. The class categories existing over the study area are agriculture, buildup, and water. The data is acquired on 19 February 2018 using the European Space Agency (ESA) based on Sentinel-2. It offers the information in twelve different spectral bands such as (a) 4 VIS and NIR bands at 10 m of spatial resolution, (b) 6 Red and SWIR bands at 20 m of spatial resolution, and (c) 3 atmospheric correction bands at 60 m of spatial resolution. The sentinel dataset offers a range of applications in various scientific domains.

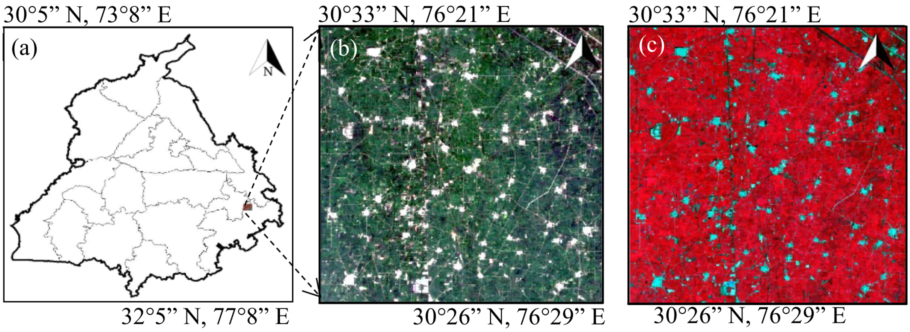

Fig. 1. Study area: (a) Punjab state (India) map highlights the study area, (b) 19-Feb-2018 Sentinel-2 imagery at RGB 432 (Natural color), and (c) 19-Feb-2018 Sentinel-2 imagery at RGB 843 (color infrared that highlights the healthy and unhealthy vegetation). (Color figure online)

3 Methodology

The flowchart of the proposed methodology is shown in Fig. 2 which involves the three basic steps: (a) Pre-processing that involves the area of interest (AOI) acquisition from atmospherically and radiometrically correction sentinel-2 data, (b) implementation of deep learning module to train the model, (c) classification. This framework is designed specifically to work with remotely sensed imagery to solve geographic problems through deep learning technologies [33]. The model must be trained to look for specific features using a set of input label raster that indicates know samples of the features [34].

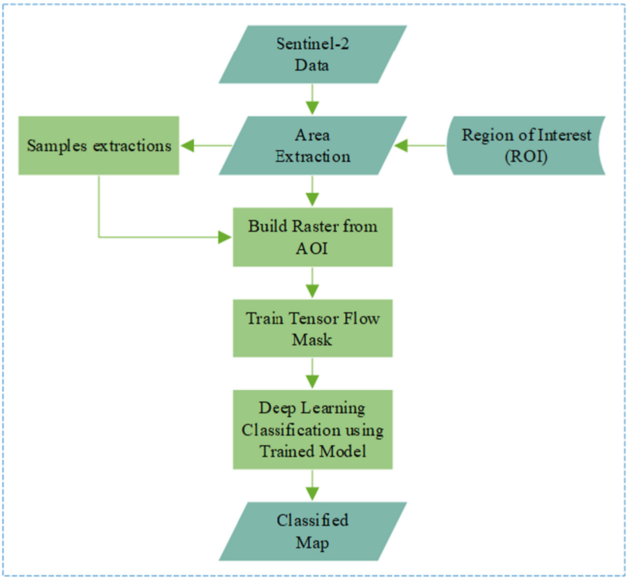

Fig. 2. The flowchart is shown the proposed methodology of the deep learning algorithm.

3.1 Preprocessing

In the present work, we are dealing with the agricultural land and therefore, the data has been pre-processed using the "Sen2cor" software tool for performing atmospheric and radiometric corrections [25]. Afterward, the AOI is extracted from the Sentinel-2 tile and fed to the deep learning model.

3.2 Deep Learning Process

Initially, the sample was extracted from the input dataset with the knowledge of field data and then, builds the raster with the help of training samples. Afterward, the Tensor Flow model is used to train the models using specific parameters. Once the model is trained, then it is used as the input to the classification procedure. It is noted that while implementing the deep learning process, the computer specification includes the Intel Xeon 3.2 2400 MHz 8.25 4C CPU, 16 GB of RAM, 512 GB of SSD, and NVIDIA Quadro P620 2 GB (4) MDP GFX.

3.3 Classification

Once the activation output is obtained, the classified maps have been generated using the automatic Otsu threshold method for each class category i.e. build-up area, agricultural, water, and rest all the categories have been assigned to mixed categories.

4 Experimental Analysis

The methodology shown in Fig. 3 was applied to process the dataset sentinel-2. There after the processed dataset was further analyzed to map in the form of classified dataset. To get the desired classified dataset such as vegetation, water and build-up area the classification scheme has been performed. The land cover regions were generated for each of the deep learning-based classification approaches for each category separately i.e. (a) vegetation area, (b) buildup area, and (c) water area, respectively [35].

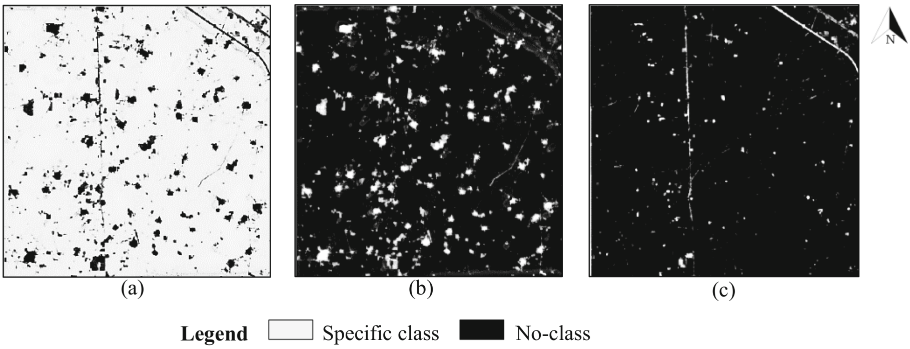

Fig. 3. Deep learning classified fractional maps (a) Vegetation area; (b) Build-up area; and (c) water area.

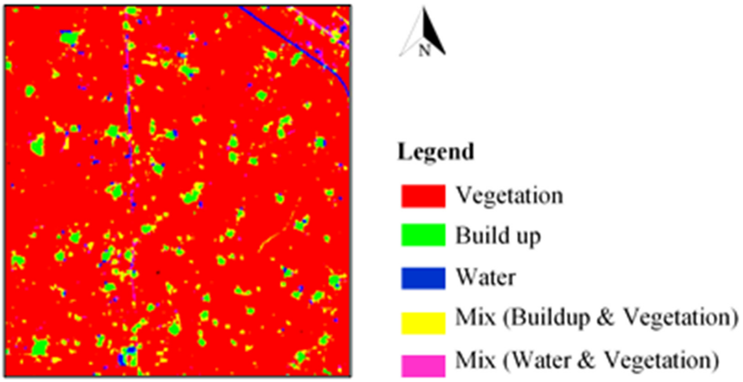

Fig. 4. Deep learning algorithm classified output after Otsu threes holding function.

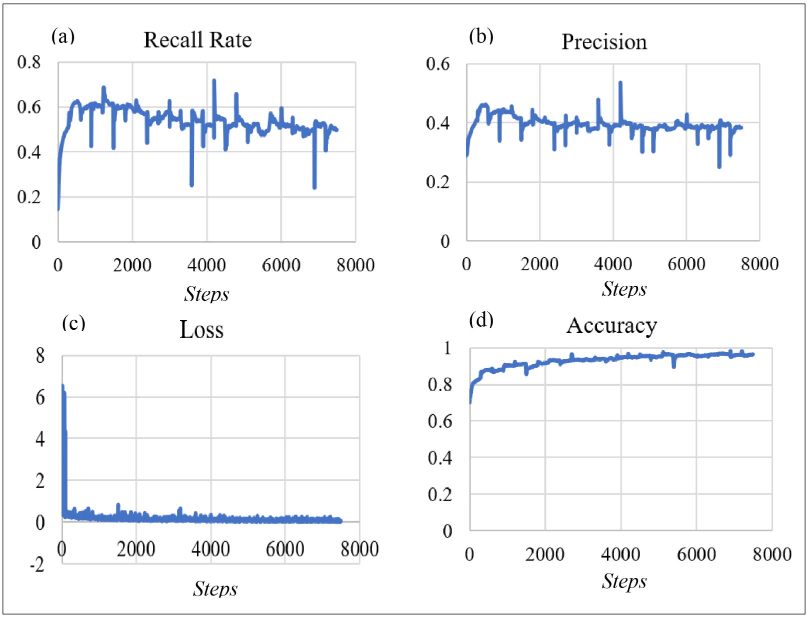

Fig. 5. The average training model recall-rate, precision, loss, and accuracy of 100 epochs for the 10 k folds.

From Fig. 4, the thematic map derived from sentinel-2 and additional data using deep learning classification algorithm show the variation in vegetation, buildup, water, mix (buildup & vegetation), and mix (water & vegetation) [36]. The main reason behind the existence of mixed categories due to limited spatial resolution. District Fatehgarh Sahib and Patiala had the samples to be collected of total number and were the effective category within the study area [37].

Moreover, the statistical analysis has also been computed for deep learning algorithms such as recalls rate, precision, loss, and accuracy. Figure 5 represents the statistical analysis to highlight the performance of the deep learning model. From the statistical analysis, the validated precision (88% accuracy) and average (98% accuracy) at the 100th epoch for 10 k folds and while the loss and recall rate started to raise. To hand was no significant raise or reduction after the 100th epoch, and the training was completed at that epoch to attain the highest accuracy possible without any over-fitting the network [21].

5 Conclusion

This study highlights the performance of a deep learning algorithm for agricultural land using the Sentinel-2 satellite dataset. The deep learning algorithm confirmed that all classes contributed in the classification process. Also, all the mixed categories have been separated to improve the accuracy of classification [38]. From the present study, it has been concluded that deep learning plays a significant role in the extraction of accurate class categories from satellite images. However, the results may be affected due to the limited spatial resolution of the satellite dataset. It is expected that different vegetation types could be explored using high spatial resolution and hyperspectral dataset. This research has a wide contribution in agriculture field to decide the area suitable for crop field. This research will prove to be more useful in finding areas that burn straw. Future recommendations also involved the exploration of deep learning algorithms for different land-use and land-cover types using different sensors at the global level.

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