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# Deep neural network for crop classification using multitemporal data: A case study of Sialkot, Pakistan

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**Abstract**

Agriculture is a fundamental sector in Pakistan's economy, providing employment to a large portion of the population and significantly contributing to national income. However, traditional methods of crop yield estimation, such as crop-cutting surveys, are outdated, labor-intensive, and often result in inaccuracies. These methods also tend to be time-consuming, which can hinder timely decision-making in agricultural planning and resource management. The advent of freely available spatial data, particularly from remote sensing technologies, coupled with artificial intelligence, presents an opportunity to transform the way crop yields are monitored and predicted. This study investigates the integration of Geographic Information Systems (GIS) and remote sensing imagery with deep learning techniques specifically Convolutional Neural Networks (CNN) and Satellite UNET, to enhance the accuracy and efficiency of crop type classification and yield estimation. By leveraging artificial intelligence, the proposed method not only automates the process but also improves the precision of yield predictions compared to traditional approaches. Initial findings suggest that the application of deep learning models to remotely sensed data allows for real-time monitoring, enabling quicker and more informed decisions regarding food production and resource management. The primary objective of this study is to develop a reliable, scalable tool for crop yield estimation in Pakistan, facilitating timely responses to potential food shortages and contributing to the effective management of food security. This innovative approach could revolutionize agricultural practices in Pakistan, offering a modern solution to address both current and future challenges in the sector.

**Keywords:** Classification, CNN, Deep learning, Random Forest, Satellite UNET, Sentinel2A, SVM

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## Introduction

Agriculture is humanity's oldest and most vital practice for survival (Ali et al., 2021; Iqbal & Qureshi, 2021). The increase in population in recent years has resulted in increased demand for agricultural products (Mehmood et al., 2021. For a developing country like Pakistan, agriculture contributes significantly towards the economic growth of the country where it contributes 22.04% towards the GDP and offers employment to 35.9% of the population in the sector (Usman, 2016). The livelihood of people living in rural areas is significantly dependent on the agriculture as they are either directly or indirectly associated with this field and being an exclusive sector, which combines our business innovativeness and modes of life, agriculture sector considerably serves, especially in developing countries towards poverty reduction, industrial uprising, food security along with economic growth (Gardner et al., 2010).

Owing to the shift in food consumption patterns and rapid population growth, the demand for increased agricultural products is all time high and poses a great deal of threat to the countries with scarce agricultural resources (van Beek et al., 2010; Noroz et al., 2021). Although Pakistan is blessed with abundant agricultural resources, however, the accelerated growth of population in the region has a direct impact on its agricultural products supply and demand ratio (Mehmood et al., 2020). According to the recent census-2017, the population of Pakistan is 207.68 million and to cater the increasing food demand of the population effectively, it is the need of time to take extensive measures to address the food shortage issues that the country may face in the long run.

The integration of technology and E-Governance has proved to be a handful tool towards making timely informed decisions, from monitoring to mitigating disasters and even averting potential calamities before they hit the general population. The introduction of Remote Sensing and GIS in agriculture field has helped a great deal in understanding factors affecting agricultural production by integrating statistical methods and modelling techniques. One of the important and noticeable practice in improving farming practices and optimizing amounts of inputs for best crop performance while keeping the least environmental impacts in mind is the use of Precision Agriculture (Ge et al., 2011). However, to address the general repetitive nature of RS and GIS which makes the whole process time consuming as well as somewhat tiresome, the professionals these days are focused on adopting more automated approach. To achieve that purpose, automation of machine learning and deep learning is being implemented into agriculture to fulfil this demand without depleting the environment's resources (Mehta, 2016). The concept of machine learning along with deep learning is currently the hot topic among the masses.

Deep learning, a rapidly evolving field of artificial intelligence, has transformed several industries, including agriculture, by automating traditional methods and improving precision (Sharma, 2019; Wason, 2018). In agriculture, its applications span crop classification, yield estimation, disease detection, and resource management. Emerging technologies like Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Artificial Neural Networks (ANNs) offer advanced capabilities for analyzing large datasets which although takes more time to process but enhances decision-making processes, and optimize agricultural productivity (Attri et al., 2023). These techniques outperform traditional machine learning methods by automating complex tasks with greater accuracy, making them indispensable for tackling pressing agricultural challenges such as food security and efficient resource management.

A prominent area where deep learning excels is in crop yield prediction, which involves integrating data from diverse sources like weather patterns, soil conditions, and socio-economic factors. For instance, machine learning models like Random Forest (RF), AdaBoost (AB), and Gradient Boost (GB), coupled with Randomized Search cross-validation, have been used to predict the yields of key crops such as barley, oats, rye, and wheat. These models, which utilize satellite data from NASA missions like GPCP and GLDAS, have shown excellent transferability across different regions and environmental conditions, achieving a remarkable accuracy of $R^2$ max = 0.9 (Asadollah et al., 2024). Such advancements have proven critical in addressing food security issues by enabling real-time yield estimation and improving water resource allocation, key elements for sustainable agricultural development.

In addition to yield prediction, deep learning has significantly advanced the field of crop-type mapping through the integration of spatiotemporal data from remote sensing technologies like Sentinel-2, Landsat-8, and Sentinel-1. Multitemporal and multispectral data provide valuable insights for large-scale crop identification across seasons. For example, a 3D U-Net model has been developed to fuse spatial and temporal features for crop-type mapping, achieving an impressive classification accuracy of 94.5% (Wittstruck et al., 2024). Similarly, the Deep Supervised Hierarchical (DSH) model, incorporating DeepLabV3+, channel self-attention, and histogram matching, has enhanced spatial and spectral resolution, yielding an average accuracy of 90.9% across diverse landscapes in regions like China, the U.S., and France (Che et al., 2024). Furthermore, deep learning has shown great promise in mapping complex agricultural environments such as rainfed, smallholder farms where high crop diversity complicates spatiotemporal distribution. Hybrid machine learning models like RF, Support Vector Machines (SVM), and Classification and Regression Trees (CART), deployed on platforms like Google Earth Engine, have been highly successful in mapping such diverse crop patterns, even in regions with limited ground-truth data (Gumma et al., 2024).

The primary contributions of this research are threefold. First, it integrates advanced deep learning models with spatiotemporal remote sensing data for crop-type mapping and yield prediction in Sialkot, Pakistan. Second, it introduces a scalable framework that enhances accuracy while addressing the computational and data limitations prevalent in developing regions. Lastly, this study aims to establish a reliable tool for real-time agricultural monitoring, providing actionable insights to improve food security and sustainable agricultural practices in Pakistan.

## Materials and Methods

### Study area

The district of Sialkot in Punjab Province, Pakistan, was strategically selected for this study due to its extensive agricultural activity and its suitability for satellite-based crop monitoring. Sialkot is located between 32°34'15.2"N 74°27'57.9"E and 32°24'12.7"N 74°38'48.1"E, with the Indian border running along the eastern side. The region's rich soils, combined with its prominent agricultural production, including rice, wheat, and potatoes, make it an ideal area for studying crop health using remote sensing technologies. This study leverages data from the Sentinel-2 satellite (Table 3), which regularly passes over Sialkot. Sentinel-2 provides multispectral imagery with a revisit time of 5 days and a spatial resolution of 10 meters, making it well-suited for tracking the phenological stages of crops during critical periods of the growing season. The satellite's ability to capture temporal variations is essential for assessing crop growth dynamics, particularly in large, cultivated areas like Sialkot, which had 399,000 hectares under cultivation in 2017, with 138,000 hectares dedicated to rice and 203,000 hectares to wheat (Punjab Development Statistics, 2017-18). The spatial variability within the district, divided into four administrative tehsils—Daska, Pasrur, Sambrial, and Sialkot—introduces diverse cropping patterns and environmental conditions, further justifying the use of remote sensing for monitoring. Sentinel-2's imagery allows for the application of vegetation indices such as NDVI, which is crucial for detecting differences in crop health across this varied landscape.

Additionally, the warm climate, with temperatures reaching up to 41.8°C in June, combined with the district's dense population (1,291 people per square kilometer) and the total area of 3,016 square kilometers, provides a challenging yet insightful environment for studying the impacts of climate and population pressures on agricultural productivity. These factors make Sialkot a compelling choice for satellite-based crop monitoring, enabling the capture of spatial and temporal variations that are critical for understanding crop conditions. The data acquired for this study was collected in stages since the essence of each piece of information differed which contains crop points from the crop reporting office, survey sample points, and satellite images of sentinel2A. The survey data was gathered in the field using Google Sheets and then combined with crop field points provided by the crop reporting office, which later verified, processed, and analyzed. Imagery retrieved from Google Earth Engine (GEE). GEE has proven effective in processing and analyzing large-scale satellite data for crop classification (Shelestov et al., 2017; Zhang et al., 2022). Researchers have utilized various satellite sources, including Sentinel-2 and Landsat, to create high-resolution crop maps (Peterson & Husak, 2021; Wijaya et al., 2023). These studies have employed different classification methods, such as random forests, support vector machines, and neural networks, to achieve accurate crop type identification (Shelestov et al., 2017; Zhang et al., 2022). The integration of historical crop data, like the Cropland Data Layer, has been shown to improve classification accuracy and reduce the need for extensive ground truthing (Zhang et al., 2022).

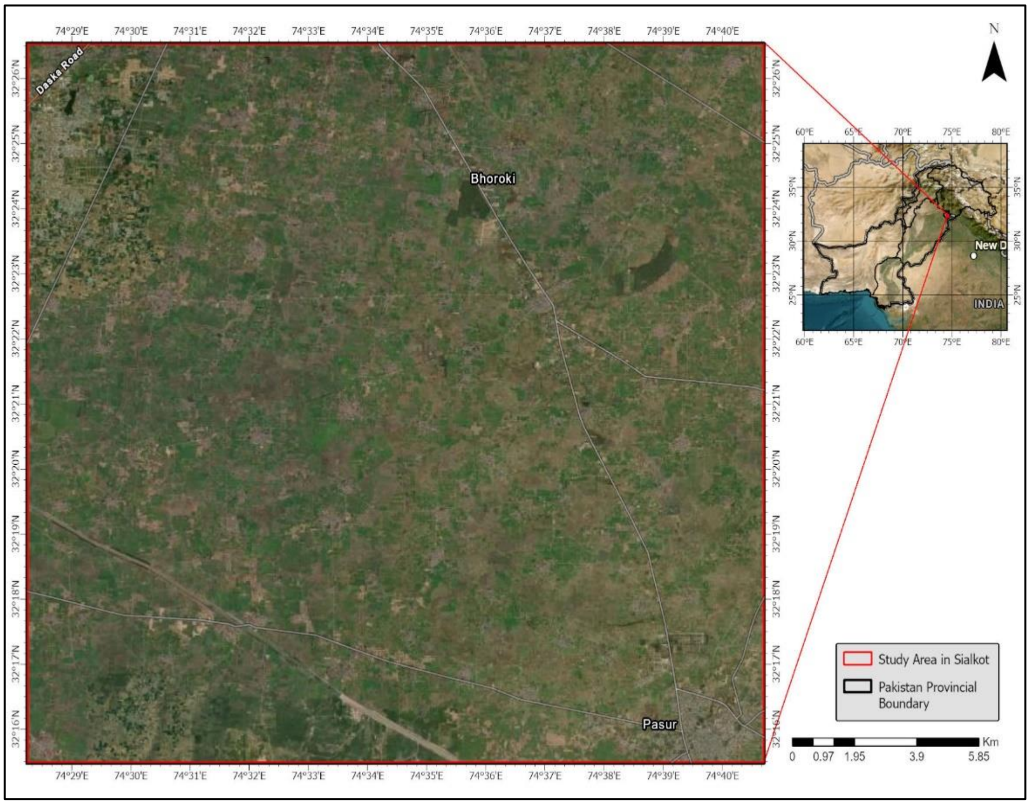


**Fig. 1** Study area in district Sialkot

### Tools and techniques

The identification of appropriate methods and technologies for this study was one of the first activities in conducting it. Individual goals necessitated various types of research tools. The parts that follow describe the techniques being used in relation to the research goals, such as conducting a survey, developing a fitting model for crop classification, and comparing various classification techniques. Two or more band's spectral reflectance are used to calculate satellite-based indices (Clerici et al., 2017). To demonstrate relative abundance of feature of interest (Leaf area, canopy chlorophyll content estimation and vegetation cover), these indices are being incorporated. It was helpful in clearly differentiate the crop and non-crop area, whereas NDVI spectral profiles of the mature season were analyzed during the mask preparation of different crops.

### Data acquisition

The dataset used for this study was divided into three key components: Crop Reporting Data, Ground Survey Points, and Satellite Imagery (Table 1). The Crop Reporting Data was acquired from the crop reporting office, providing information such as crop type, crop code, acquisition date, estimated area, and geographic coordinates. This data is commonly used in agricultural studies to identify crop types across specific locations and has proven valuable for mapping crop patterns based on calendar dates. To validate the accuracy of the Crop Reporting Data, a ground survey was conducted, selecting 100 random points to compare with the reporting data. This validation step enabled the creation of a local crop calendar (Table 2) specific to the study area (Fig. 1), enhancing the accuracy of crop classification efforts (Table 2). For satellite imagery, Sentinel-2A data was selected due to its high spatial and temporal resolution, which is well-suited for agricultural monitoring. Using Google Earth Engine, the process was semi-automated to ensure efficient data retrieval over the period from October 1, 2017, to May 31, 2020. Sentinel-2's imagery is widely used for crop classification due to its capability to capture phenological changes in crops, making it highly compatible with deep learning models for precise crop mapping. While some atmospheric limitations such as cloud cover were encountered, the data remained robust for the intended analysis.

The map presented below illustrates the geographical locations surveyed between December 20, 2017, and February 23, 2018. Each point on the map represents a specific site where data was collected during this period. Sentinel-2 satellite imagery, with a spatial resolution of 10 meters per pixel, was utilized for the survey, providing high-resolution data for detailed spatial analysis. The sample size, based on pixel resolution, is reflected on the map, offering a clear depiction of the area surveyed. By incorporating both temporal and spatial details, this map enhances the contextual understanding of the survey's scope and adds significant value to the overall research.

**Table 1** Dataset used in this research

| Resource | Dataset | Data type | Data quality |
|---|---|---|---|
| Copernicus Open Access Hub | Sentinel 2A/2B | Raster | Atmospheric Corrected |
| Crop Reporting Office | Crop Sample Points | Point | Validated with survey points |
| GPS data | Crop Field Demarcation | Points | Accurate |
| Survey of Pakistan | District boundary of Sialkot | Polygon | Accurate |

**Table 2** Local crop calendar for major crops in the region

| Start date | End date | Crop | Start date | End date | Crop |
|---|---|---|---|---|---|
| 2017-11-24 | 2018-04-26 | Wheat | 2018-06-07 | 2018-11-19 | Rice |
| 2017-11-19 | 2018-05-01 | Wheat | 2018-07-07 | 2018-11-24 | Rice |
| 2017-11-24 | 2018-04-28 | Wheat | 2018-07-07 | 2018-11-24 | Rice |
| 2017-11-24 | 2018-04-28 | Wheat | 2018-07-07 | 2018-11-19 | Rice |
| 2017-11-24 | 2018-05-01 | Wheat | 2018-07-07 | 2018-11-19 | Rice |
| 2017-11-24 | 2018-05-01 | Wheat | 2018-07-07 | 2018-11-19 | Rice |
| 2017-12-07 | 2018-04-28 | Wheat | 2018-07-07 | 2018-11-19 | Rice |
| 2017-12-07 | 2018-04-28 | Wheat | 2018-07-07 | 2018-11-24 | Rice |
| 2017-12-07 | 2018-05-31 | Wheat | 2018-07-07 | 2018-11-19 | Rice |
| 2017-12-07 | 2018-04-28 | Wheat | 2018-07-07 | 2018-11-19 | Rice |
| 2017-12-07 | 2018-05-08 | Wheat | 2018-07-07 | 2018-11-19 | Rice |
| 2017-12-07 | 2018-04-28 | Wheat | 2018-07-07 | 2018-11-24 | Rice |
| 2017-12-07 | 2018-04-28 | Wheat | 2018-07-27 | 2018-11-19 | Rice |
| 2017-12-07 | 2018-04-28 | Wheat | 2018-07-07 | 2018-12-02 | Rice |
| 2017-12-07 | 2018-04-28 | Wheat | 2018-07-25 | 2018-11-19 | Rice |
| 2017-11-24 | 2018-04-28 | Wheat | 2018-07-07 | 2018-11-24 | Rice |
| 2017-12-07 | 2018-04-28 | Wheat | 2018-07-07 | 2018-12-19 | Rice |
| 2017-12-07 | 2018-04-28 | Wheat | 2018-07-07 | 2018-12-24 | Rice |
| 2017-12-07 | 2018-04-28 | Wheat | 2018-07-07 | 2018-12-02 | Rice |
| 2017-12-07 | 2018-05-08 | Wheat | 2018-07-07 | 2018-12-02 | Rice |
| 2017-11-24 | 2018-04-28 | Wheat | 2018-07-07 | 2018-12-02 | Rice |
| 2017-12-07 | 2018-05-01 | Wheat | 2018-07-05 | 2018-12-02 | Rice |
| 2017-12-07 | 2018-04-28 | Wheat | 2018-07-27 | 2018-12-02 | Rice |
| 2017-12-07 | 2018-04-28 | Wheat | 2018-07-07 | 2018-12-09 | Rice |
| 2017-12-07 | 2018-04-28 | Wheat | 2018-07-07 | 2018-12-09 | Rice |
| 2017-11-24 | 2018-04-28 | Wheat | 2018-07-07 | 2018-11-24 | Rice |
| 2017-12-07 | 2018-04-28 | Wheat | 2018-07-25 | 2018-11-19 | Rice |
| 2017-12-07 | 2018-04-28 | Wheat | 2018-07-07 | 2018-11-24 | Rice |
| 2017-12-07 | 2018-04-28 | Wheat | 2018-07-07 | 2018-11-24 | Rice |
| 2017-12-07 | 2018-04-28 | Wheat | 2018-07-25 | 2018-12-09 | Rice |

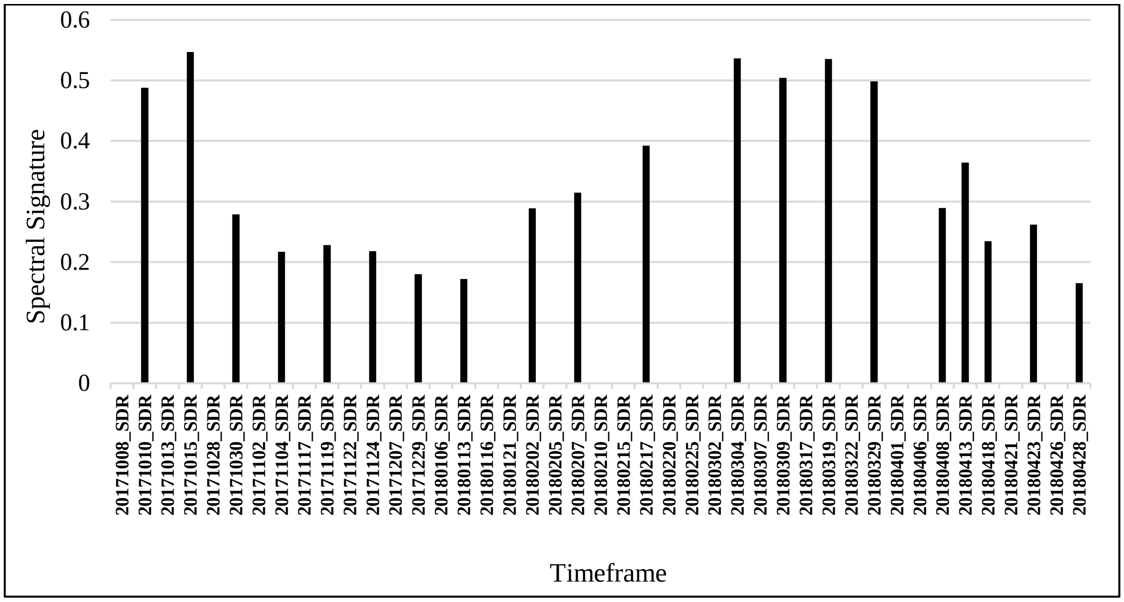


**Fig. 2** Spectral signature of wheat

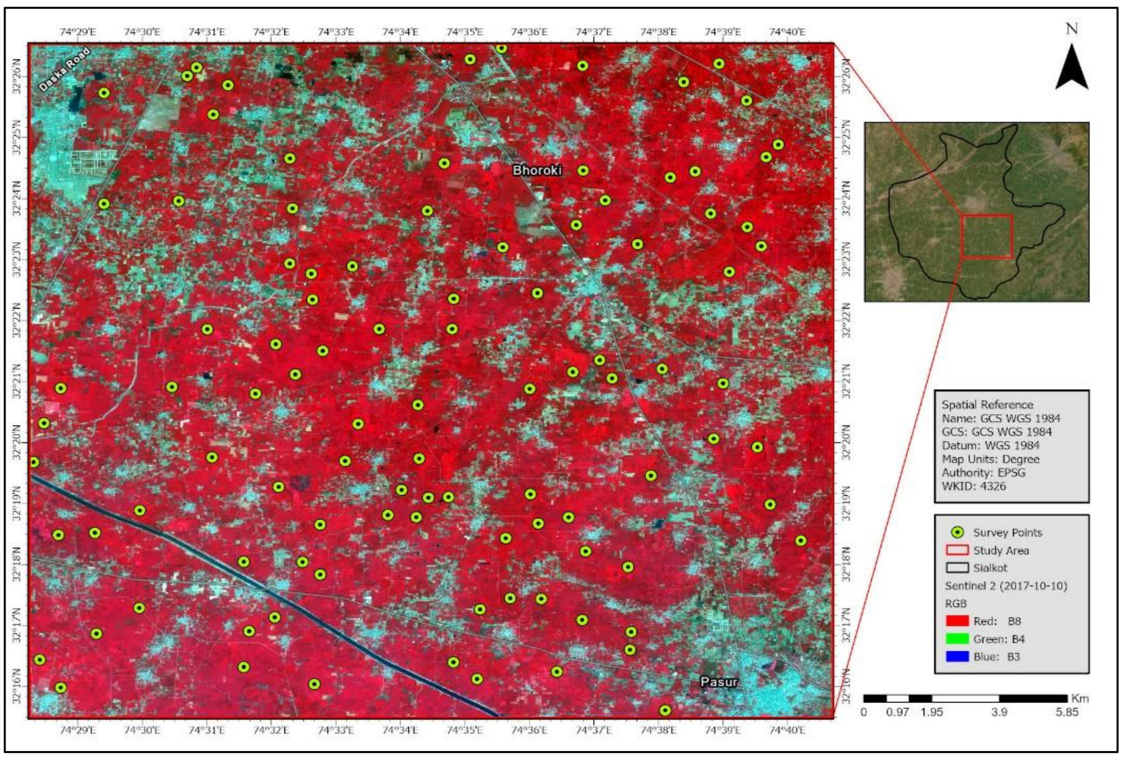


**Fig. 3** Distribution of sample points in study area

### Satellite datasets

The Sentinel-2 (S2) comprising of S2A and S2B, two identical satellites, captures high resolution optical imagery composed of three bands at 60m, six bands at 20m and four spectral bands at 10m resolution. The constellation is equipped with a multispectral instrument (MSI) to capture this optical imagery. The S2 sensor captured optical images while cloud-free tiles were downloaded in Level-2A (L2A), providing orthorectified Bottom-Of-Atmosphere (BOA) reflectance with sub-pixel multispectral registration. 60m resolution bands were excluded due to their sensitivity to clouds and aerosol while nearest neighbor approach was used to resample 20m spectral bands to 10m preserving original pixel values.

**Table 3** Sentinel-2 (S2) imagery used in this research

| Image date (Wheat) | Year | Image date (Rice) | Year |
|---|---|---|---|
| 2018-01-27 | 2018 | 2018-08-26 | 2018 |
| 2018-02-17 | 2018 | 2018-09-05 | 2018 |
| 2018-03-04 | 2018 | 2018-09-20 | 2018 |
| 2018-03-09 | 2018 | 2018-09-30 | 2018 |
| 2018-03-19 | 2018 | 2018-10-05 | 2018 |
| 2018-03-29 | 2018 | 2018-10-15 | 2018 |
| 2019-01-28 | 2019 | 2018-10-25 | 2018 |
| 2019-02-22 | 2019 | 2019-08-21 | 2019 |
| 2019-02-27 | 2019 | 2019-08-26 | 2019 |
| 2019-03-09 | 2019 | 2019-10-10 | 2019 |
| 2019-04-08 | 2019 | 2019-10-15 | 2019 |
| 2020-02-07 | 2020 | 2019-10-25 | 2019 |
| 2020-02-17 | 2020 | 2019-10-30 | 2019 |
| 2020-02-22 | 2020 | 2020-09-19 | 2020 |
| 2020-03-03 | 2020 | 2020-09-29 | 2020 |
| 2020-03-18 | 2020 | 2020-10-04 | 2020 |
| 2020-03-23 | 2020 | 2020-10-14 | 2020 |
| | | 2020-10-19 | 2020 |
| | | 2020-10-24 | 2020 |

**Data pre-processing**

The acquired dataset, including crop reporting points, ground survey points and satellite imagery underwent preprocessing. Later surveys were performed to get ground data for the verification using random points. To conduct surveys, google sheets were used for data entry and being integrated with google forms, it helps to integrate google form with google sheets, only APIs are required to fetch data from form to sheets. These data points (Fig. 3) were analyzed, and anomalies were removed. To integrate ground survey points with crop reporting points, overlay analysis was used and the local crop calendar (Fig. 2) for the study area was generated with provided time interval. For satellite imagery COPERNICUS/S2 was being used having 10m resolution. This satellite acquires high-resolution multispectral images for a variety of purposes, including vegetation, soil and water cover monitoring, land cover change, and humanitarian and catastrophe risk assessment. The satellite imagery was acquired through Google Earth Engine, which offers the advantage of automated preprocessing prior to download, streamlining the workflow and reducing manual effort. Optical remote sensing data is highly susceptible to atmospheric disturbances, which significantly alter the spectral properties of radiation reaching the sensor (Pacifici et al., 2014), (Schowengerdt, 2006). To mitigate these atmospheric effects and enhance the accuracy of reflectance values, atmospheric correction procedures, aerosol scattering, water vapors absorption and cloud masking were applied to the dataset. Moreover, to calibrate the pixel values and/or compensate for faults in the values, radiometric correction was used. The method increases the quality and interpretability of remote sensing data. When comparing several data sets across time, radiometric calibration and adjustments are very crucial. To create a planimetrically accurate image, orthorectification removes the effects of picture perspective (tilt) and relief (terrain). The orthorectified image that results has a consistent scale and features that are shown in their "real" places.

The heart of many earth observation efforts is optical remote sensing imaging. Many applications take use of the satellite data's regular, consistent, and global-scale characteristics, such as farmland monitoring, climate change assessment, land-cover and land-use categorization, and catastrophe assessment. However, one major issue, cloud cover, has a significant impact on the temporal and geographic availability of surface observations. Since decades, researchers have been studying how to remove clouds from optical pictures. In the process cloud mask has been used with less than 10% cloud cover area in google earth engine which still left behind some missing data in the imagery. These missing values were the patches in the tile with missing data in varying sizes which made it even harder to detect and remove. Python script was written to identify all the tiles dataset with missing values and were removed from the training and testing part. Four selection criteria were applied before downloading data from Google Earth Engine: filter date, filter clouds, filter boundary and apply cloud mask. The date range criterion defined the temporal extent for the dataset, with the earliest allowable date set to 2015. The cloud coverage filters excluded images containing cloud cover above a specified threshold, ensuring higher-quality data and reducing irrelevant entries. For the spatial boundary, a 20×20 $km^2$ area of major agricultural land was selected to minimize uncertainties. Finally, a cloud mask was applied to all remaining images to further eliminate any residual cloud interference.

In the later step, Normalized Difference Vegetation Index was calculated for each of the image tile using band B8 and B4. Band 8 represents near infrared whereas band 4 is red band which are used to calculate the NDVI. A local crop calendar was created by overlaying a stack of NDVI raster with systematically generated random points in the region of interest. The random points were generated using a stratified random sampling approach to ensure that all the points are uniformly distributed while avoiding non-cropland regions such as barren land. The values of NDVI were stacked with the feature class of random points using a python script, resulting in a local crop calendar for the study region from 02-11-2017 to 01-07-2020. Each raster's NDVI data were used to produce a continuous graph for each random point. This graph assisted in the identification of crops at all phases during the sowing, growing, and harvesting periods. Wheat and rice were selected as the two major crops of rabbi and kharif, respectively.

## Methods

### Random Forest (RF) classification

Because of its easy parametrization, feature significance estimation in classification, and quick computation time, the RF classifier was chosen for this study [3]. As a result, it is discussed how to optimize RF hyperparameters for vegetation mapping. RF has numerous hyperparameters that enable users to modify the forest's structure and size (ntree) as well as its unpredictability (for example, the number of random variables used in each tree—mtry). The ntree and mtry parameters' default values are 500 and the square root of the number of input variables, respectively. As a result, for hyperparameter tuning, a grid search technique with cross validation was utilized in this study, and optimal parameter values were chosen as those that gave the best classification accuracy.

### Support vector machine

The Support Vector Machine (SVM) is a popular pattern recognition algorithm. As supervised learning, it may be used to solve classification and regression issues. Multi-perceptron was developed in the 1980s to create a machine learning model that can learn like a person. However, there were several issues, such as unfavorable convergence to a local optimal solution and the number of intermediate layer neurons used. SVM solves the issues by using the kernel technique on the maximum margin hyperplane (Vapnik, 2013). The Gaussian Radial Basis Function (RBF) was used as the kernel function in this research. This model was implemented using scikit-learn, a Python machine learning module (Pedregosa et al., 2011).

### Convolutional neural network

Convolutional Neural Networks (CNNs) have been around for decades (LeCun et al., 1998),arising from research into the visual cortex of the brain (Hubel & Wiesel, 1962) and traditional computer vision theory (Dalal & Triggs, 2005), (Szeliski, 2010). These have been effectively used in picture categorization since the 1990s (LeCun et al., 1998). CNNs, on the other hand, did not scale to big applications owing to technological restrictions such as a lack of hardware performance, a vast volume of data, and theoretical limits. Nonetheless, Geoffrey Hinton and his colleagues proved the ability of training huge architectures capable of learning many layers of features with more complex internal representations (Zeiler & Fergus, 2014) during the annual ImageNet ILSVRC (Krizhevsky et al., 2012) competition. CNNs have become the ultimate emblem of the Deep Learning (Lecun et al., 2015) revolution since that breakthrough success, encapsulating all the principles that drive the entire new movement.

DL has been widely employed in data mining and remote sensing applications in recent years. Due to their versatility in feature representation and automation capacity for end-to-end learning, various DL architectures were used in picture categorization research. By including autoencoders into DL models, features may be automatically retrieved for classification tasks without the use of feature building methods (Wan et al., 2017), (Mou et al., 2018). To extract spatial characteristics from high-resolution pictures for object recognition and image segmentation, 2D CNNs have been widely employed in remote sensing research (Kampffmeyer et al., 2016), (Audebert et al., 2018). 2D convolution in the spatial domain outperformed 1D convolution in the spectral domain in crop classification (Kussul et al., 2017). Multiple convolutional layers were created in these experiments to extract spatial and spectral information from remotely sensed images.

**Table 4** CNN structure of custom model used

| Layer (type) | Output shape | Param # |
|---|---|---|
| InputLayer | [(None, 11, 1)] | 0 |
| Conv1D | (None, 9, 64) | 256 |
| Conv1D | (None, 7, 128) | 24704 |
| Conv1D | (None, 5, 256) | 98560 |
| Conv1D | (None, 3, 512) | 393728 |
| Conv1D | (None, 1, 1024) | 1573888 |
| Flatten | (None, 1024) | 0 |
| Dense | (None, 2) | 2050 |

### Satellite UNET

We used an encoder-decoder network based on the Unet model, which was first used in bio-medical segmentation (Ronneberger et al., 2015) The structure resembles the letter U, as the name suggests. Unet creates a ladder-like structure by concatenating encoder feature maps with up-sampled feature maps from the decoder at each level. Our network (Satellite Unet) starts with a 5-block convolutional neural unit basis, which is then followed by a max pooling layer. After each convolutional layer, a ReLU activation function is used. A decoder receives the feature maps that have been obtained. The feature maps are up sampled by the decoder, resulting in predictions with the original spatial resolution. Each convolutional layer is preceded by an up-sampling layer in the decoder, which starts with a 5-block convolutional neural unit foundation. A ReLU activation function follows each convolutional layer. As a result, the final feature maps are input into a completely 2D convolutional layer with two classes and a ReLU activation function, as illustrated in Table 4.

The following are some of the ways that our network (Satellite Unet) differs from the traditional (Unet):

- In comparison to UNet, which has 23 convolutional layers, Satellite UNet has 19 convolutional layers.
- In Satellite UNet, the filter size is 5 5, but in standard UNet, the filter size is 3x3.
- In comparison to Unet, the total number of trainable parameters in Satellite Unet is lower.
- In Satellite Unet, the convolution operations are padded convolutions, but in Unet, the space between succeeding convolutional layers is reduced.

Our model is considerably more appropriate for crop classification because of these properties. An NVIDIA GPU with CUDA Core 1920 was utilized to train the model. Our model was evaluated on a 6-core, 2.6 GHz CPU.

## Results and Discussion

The first object of the study was based on the survey points data and satellite imagery, all the pre-processing on the point data and satellite imagery has already been discussed in earlier sections. To create these masks, initially abnormalities in the dataset were eliminated, such as null values in the images, incorrect coordinate points, incorrect crop identification etc. Later, these ground survey locations were integrated with crop reporting data, and a supervised classification was used to determine the cropped area. Only major crops were acquired, and labels for model feeding developed. The masks generated for wheat and rice for the year 2018, 2019 and 2020 are shown in (Fig. 5). All these masks carry binary data in the imagery i.e., black, and green; black color represents no data values whereas green color represents the availability of respective crop data in the mask. These masks along with satellite imagery of sentinel2A were provided to the model for training and testing. The results generated vary from 68% to 86% accuracy depending upon the model used.

In first section two popular methods of machine learning i.e., random forest and support vector machine were used to achieve the second objective of this study. Using the same system specifications stated in the earlier section, it took more than 6 hours to process and generate the output. The accuracy achieved using these two methods was lower in comparison to the other methods. The measured accuracy in these two was the lowest in all the models. Support vector machine was trained with a n samples, n features matrix and achieved a maximum training accuracy of 68.01% and testing accuracy of 67.92%, but random forest had a substantially higher training and testing accuracy of 75.28% and 75.19%, respectively. In second section same csv data were used to develop convolutional neural network that has already been discussed in the earlier section. This model was tuned enough to get a maximum of 80.71% accuracy with loss from 0.57 to 0.45, with this accuracy (Fig. 4) the predicted map (Fig. 5, Fig. 6) showed much better results if compared with random forest and support vector machine. This model had 5 Convo1D layers with a flatten and dense layer to obtain better results. Both wheat and rice have been classified with quite comprehensive results. The accuracy and loss graph in the (Fig. 7, Fig. 8), clearly represents the smaller difference between the training and testing data.

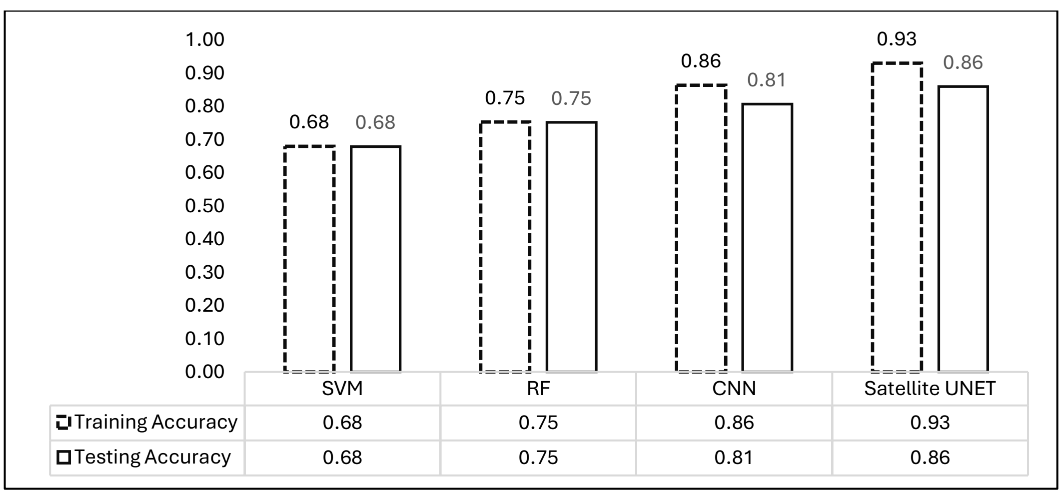


**Fig. 4** Training and testing accuracy of SVM, RF, CNN, and Satellite UNET

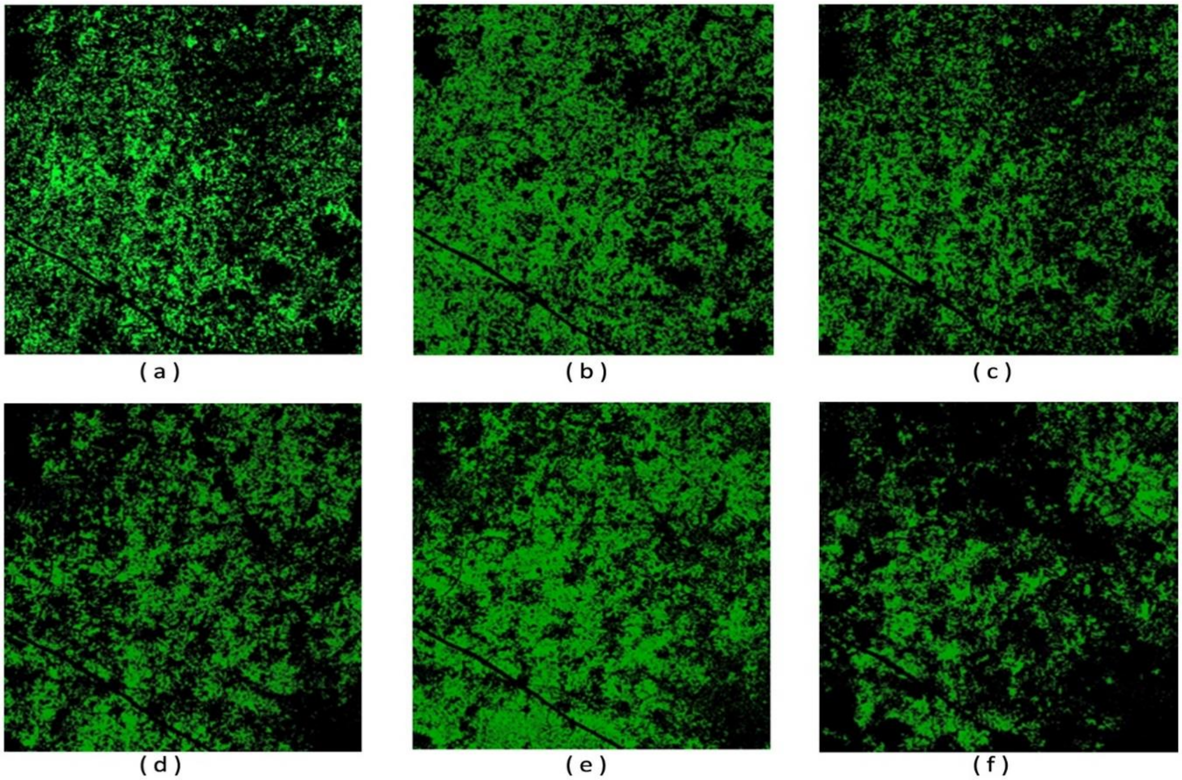


**Fig. 5** Crop masks representing crop vs non-crop area: (a) wheat 2018; (b) wheat 2019; (c) wheat 2020; (d) rice 2018; (e) rice 2019; (f) rice 2020

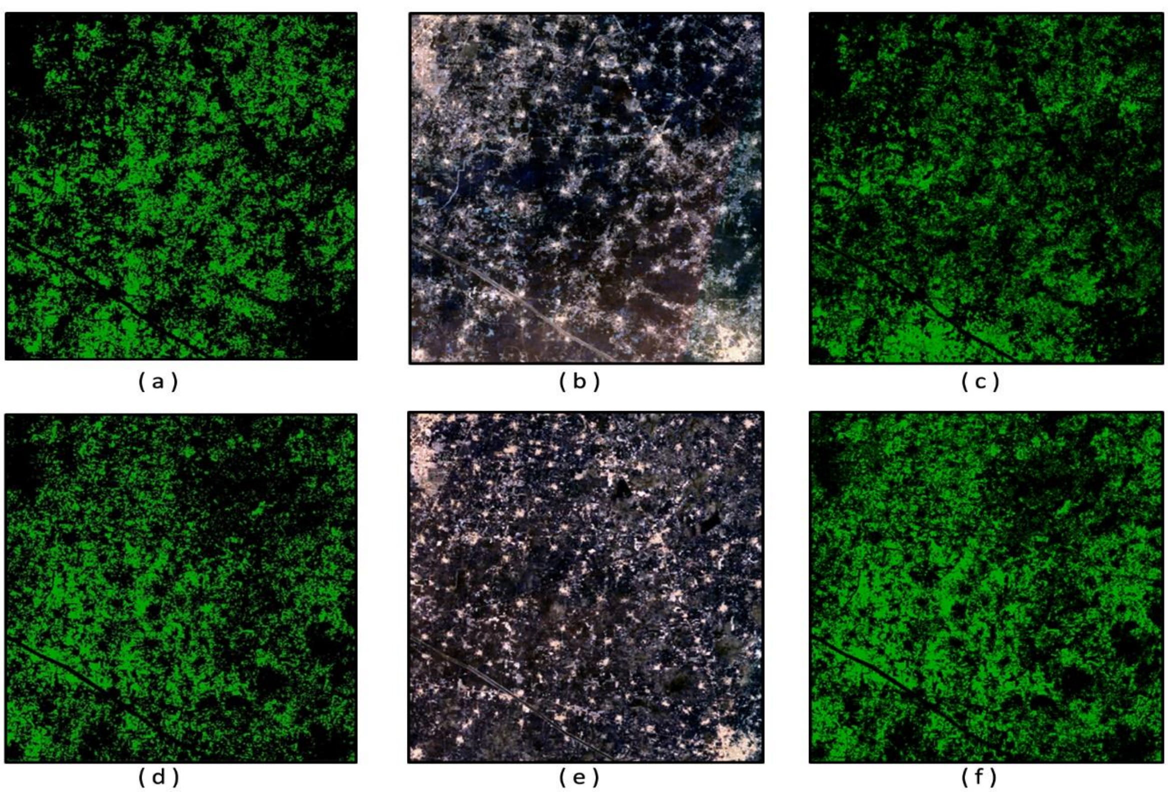


**Fig. 6** Crop Prediction masks representing crop vs non-crop area: (a) rice 2018 (b) satellite image 2018 (c) predicted rice 2018 (d) wheat 2020 (e) satellite image 2020 (f) predicted wheat 2020

The accuracy of training and testing started from 0.60 and 0.68 respectively which increased to approximately 0.75 in the next 5 epochs which highlights that the model learnt in a quicker way which the features. In the later part for next 25 epochs, it increased approximately around 0.80 for both training and testing.

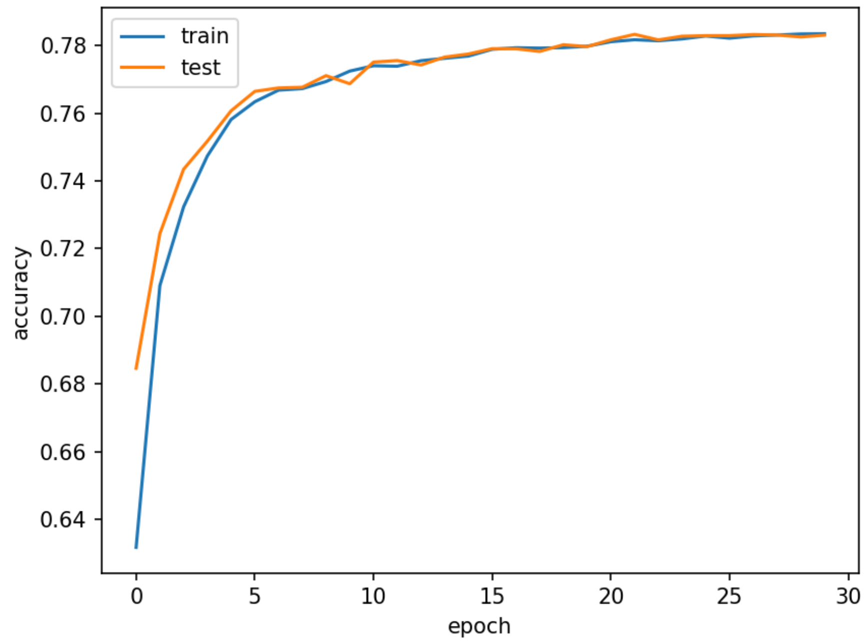


**Fig. 7** Custom CNN Accuracy for 30 epochs

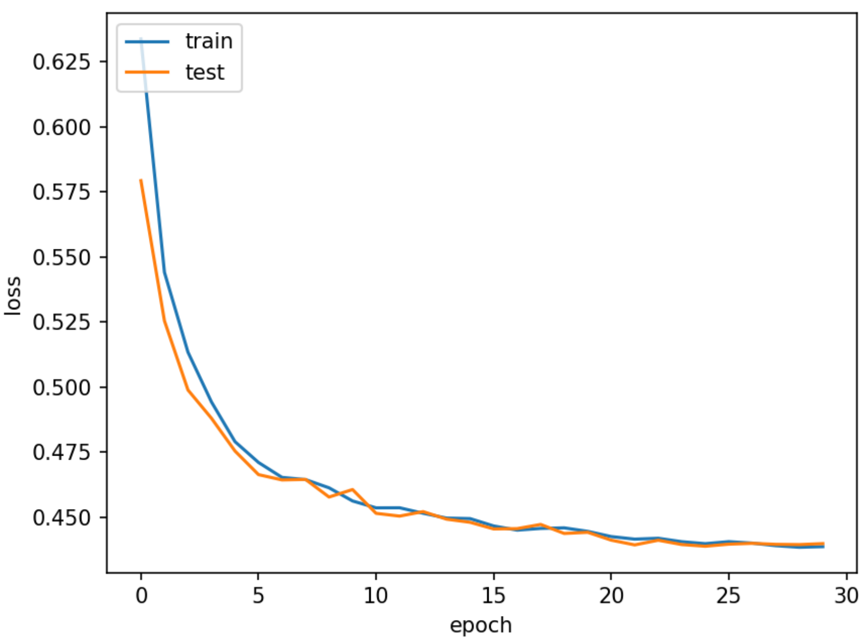


**Fig. 8** Custom CNN loss for 30 epochs

The last approach used in this study was Satellite UNET which gained the best results with the provided dataset. The maximum accuracy achieved with this fully connected dense network was 0.93 when trained with the data of a single year but it dropped to 0.86 when trained with the data of 2018, 2019 and 2020. The drop in the accuracy was due to the distribution of in the dataset due to multiple year data and the difference between them. Accuracy and loss graph are shown in the (Fig. 10, Fig. 11), respectively. In the accuracy graph it can be clearly seen that in the start there was some overfitting with the model which was in later stage dropped and a clear difference appears after 45 epochs. Overall accuracy in the study is obtained to be 86% using Satellite UNET model which has performed well with the provided dataset. Although the comparison with respect to accuracy surely gives preference to the UNET model but it also requires much power to run the model and predict the results (Fig. 9) but if these results are compared with the custom created model with 5 layers of deep network it gave 80% accuracy and can be used even on a low specification system.

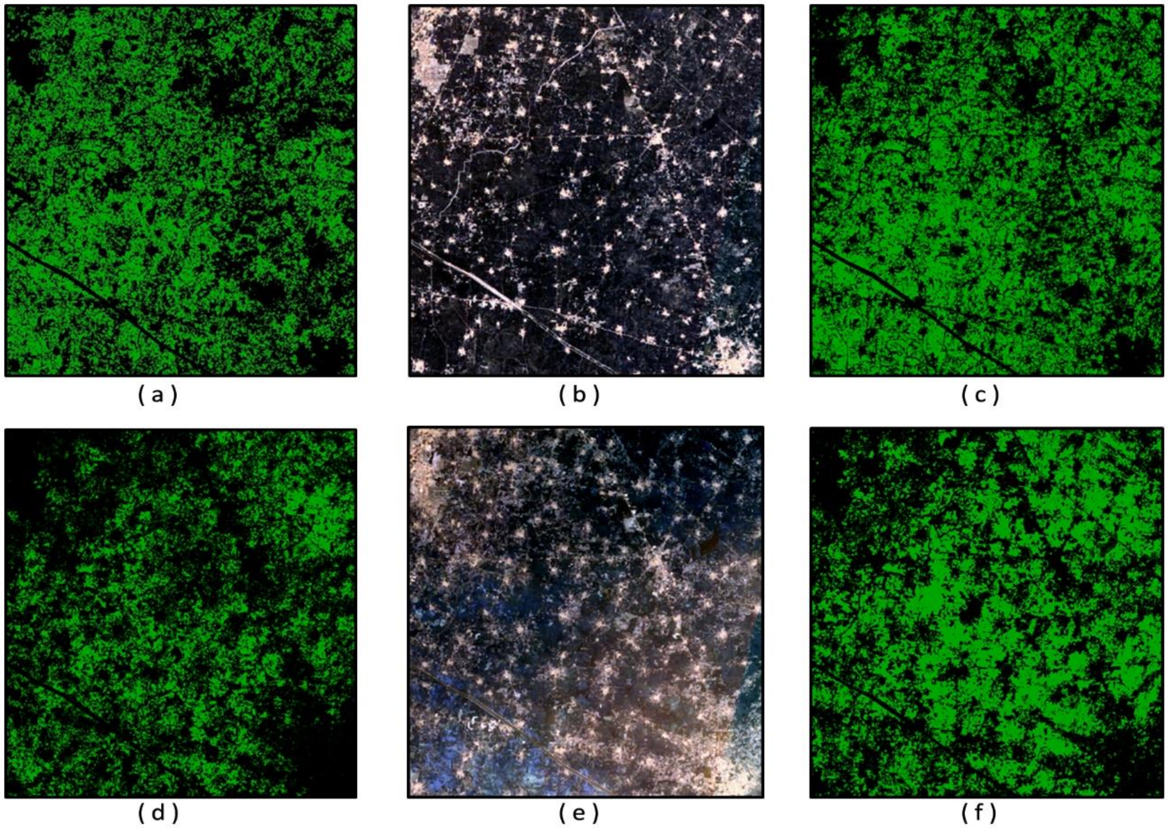


**Fig. 9** Crop Prediction masks representing crop vs non-crop area: (a) wheat 2019; (b) satellite image 2019; (c) predicted wheat 2019; (d) rice 2020; (e) satellite image 2020; (f) predicted rice 2020

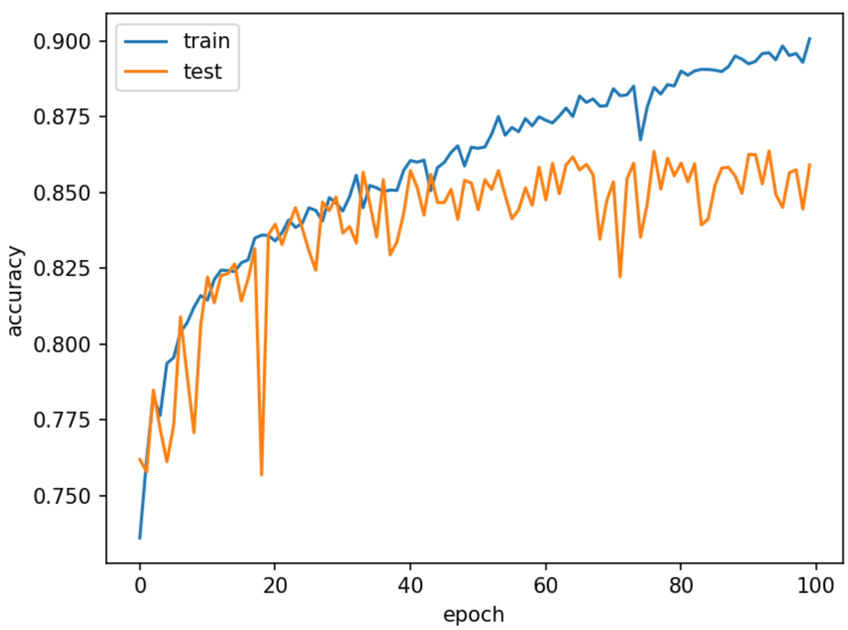


**Fig. 10** Satellite UNET Accuracy for 100 epochs. Same differences can be seen in the loss graph which started from 0.45 for training and 0.55 for testing and went to 0.1 for training and 0.32 for testing.

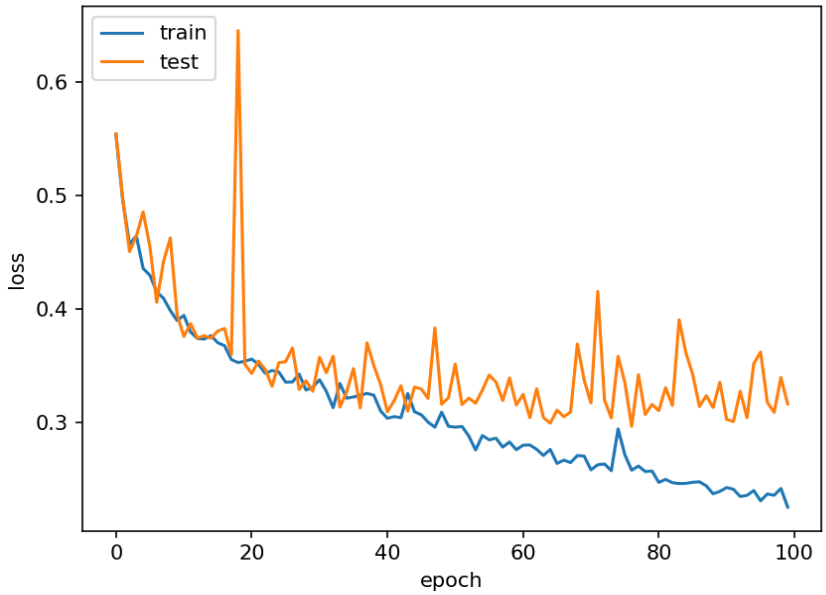


**Fig. 11** Satellite UNET Loss for 100 epochs

## Conclusion

The research project successfully developed a system to be used to recognize and classify rice and wheat using the techniques of artificial neural networks and the satellite imagery Sentinel-2A. Although the obtained accuracy was not perfect, but it helped in generating a system to distinguish between two crops. The created model was tested and verified to forecast the crop types more accurately in comparison to the classical approaches and it turn out to be a significant strong tool to be rely on. Substantial information was gathered throughout the methodology's awareness process to suggest an initial project prototype. This prototype demonstrates how to obtain the imagery using Google Earth Engine and Python, as well as a possible way to network training and testing. The addition of image processing, the switch from image classification to object identification by changing the kind of neural network from custom CNN to Satellite UNET model in the training section was the primary modifications made in the final version. It not only provided more improved results but also made the whole process more robust. The results demonstrate the project's proper development, since the project's goals were met effectively. The project automated the process of classification and improved accuracy as compared to the traditional methods. As the model is trained, even with small optimizations in the training settings and datasets, the created system can achieve acceptable accuracy percentages for further crop types. This demonstrates that, even if the acquired accuracy is lower than the accuracy of some other systems, the resultant crop classification fulfils the expectations, making it a reliable tool for effective management of food security and facilitating timely responses in potential food shortages. This innovative approach has the potential to transform agricultural practices, providing a modern solution to address both current and future challenges within the sector.

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