Object Detection and Classification Using Satellite Imagery

Six Month Training Report

Of

Sabudh Internship

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CANDIDATE'S DECLARATION

We hereby certify that we have undergone six months industrial training at SABUDH FOUNDATION and worked on project entitled, **"Object Detection and Classification Using Satellite Imagery"**, is an authentic record of our own work carried out during a period from January, 2022 to June, 2022 under the supervision of Dr. Sukhjit Singh Sehra and Mr. Vijay Garg.

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This is to certify that the above statement made by the candidates is correct to the best of my knowledge.

Sukhjit Singh
Vijay Garg

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The successful completion of any task is incomplete and meaningless without giving any due credit to the people who made it possible without which the project would not have been successful and would have existed in theory.

We would also like to take this moment to show our thanks and gratitude to one and all, who indirectly or directly have given us their hand in this challenging task. We feel happy and joyful and content in expressing our vote of thanks to all those who have helped us and guided us in presenting this project work for our Major project. Last, but never least, we thank our well-wishers and parents for always being with us, in every sense and constantly supporting us in every possible sense whenever possible

ABSTRACT

This project aims at working with satellite images and classifying them based on multiple classes such as Farms, Forests, Crops and Urban Areas. Two data-sets for the project were extracted from Sentinel Hub (open source for Satellite Image extraction) and Planet Scope, which are the designer and builder of the world's largest constellation of Earth-imaging satellites. Area of the study was considered as Chatbir, Punjab and images were taken of Sentinel-2 L2A satellite with 10m spatial and Planet Scope with 1.5m resolution for the year 2018 to 2021 excluding cloudy images. We have applied machine learning algorithms such as SVM, Random forest, XGboost, Gradient Boosting, KNN and Deep Learning algorithm (CNN-1D) for crop, Farm, Forest, Urban area classification. Multiple experiments with different combinations of feature sets as different vegetation indices were carried out to build a better model. The results showed that the augment of multi-spectral information of Sentinel-2 improved the accuracy of different class classification remarkably in Deep learning algorithm (CNN-1D), and the improvement was firmly related to strategies of feature selections and data cleaning. Compared with other indexes, NDVI index showed a higher competence in classification. The combined application of images of a year is significant for achieving optimal performance. A relatively accurate classification (overall accuracy = 0.95) was obtained by giving NDVI as a feature on the yearly data on CNN 1D model. Our resluts shows that planet scope data is giving low misclassification and higher accuracy scores than sentinel hub, because planet scope has higher (1.5m spatial resolution) compared to sentinel hub. This study gave an inspiration in selecting targeted indexes and period of images for acquiring more accurate and timelier crop and land classification. The proposed method could be transferred to larger areas as well to see the different classification for better learning.

Keywords - *Satellite Image, SVM, CNN, KNN*

LIST OF FIGURES

LIST OF ABBREVIATIONS

Abbreviation	Full Form
SVM	Support Vector Machine
CNN	Convolutional Neural Network
KNN	K-Nearest Neighbors
XGBoost	eXtreme Boosting
RF	Random Forest
CNN	Convolution Neural Network
NDVI	Normalised Difference Vegetation Index
EVI	Enhanced Vegetation Index
NDWI	Normalised Difference Water Index
GNDVI	Green Normalised Difference Vegetation Index
SAVI	Soil Advanced Vegetation Index

Contents

Chapter 1

Introduction to Organisation

Sabudh Foundation - An NGO that applies data science for social good. Sabudh Foundation is formed by the leading data scientists in the industry with the objective to bring together data and young data scientists to work on focused, collaborative projects for social benefit. Sabudh foundation is working on solving the real and high impact problems in areas such as education, governance, healthcare, and agriculture using Artificial Intelligence and Machine Learning techniques.

Data science can be used across a number of industries in order to be beneficial for the society. For example in agriculture, there are now Agro-bots and drones being used to gauge the health of the harvest that can help farmers improve their crop yield and reduce costs. With the help of advanced technologies, we're able to save 90% of the spraying costs. These technologies can help states like Punjab which has always been the food basket of India to rehabilitate food security while improving crop health.

The foundation has taken steps to involve Colleges, Universities, and Industry from the region for the social cause. Particularly, the foundation has signed academic and research-based MoUs with Punjab University, Chandigarh, GNDEC, Ludhiana, BML Munjal University, Punjab Government (Punjab Police), Punjabi University, Patiala, and Punjab Engineering College, Chandigarh.

Chapter 2

Introduction to Project

Satellite images give us a lot of information which cannot be gathered by normal images captured by camera or any other instrument on the ground. In this project the satellite images of the Chatbir area, Punjab extracted form Sentinel Hub and Planet Scope are of very much importance in order to understand the phenomenons going on the land at a large scale like deforestation, shifting of vegetation etc. Fig 2.1 shows the different bands of Sentinel 2 L2A satellite. The single Satellite image has 12 bands in it. Since different objects reflects different wavelengths, satellite gives us the advantage to take into account the different wavelengths to classify a particular object, since it has a multi spectral bands.For example if we want to classify the crop or forests we can use band 8 and band 4. It has been stated that all the satellite images are not of use because in the end what is important is that the images should provide us some information about the area we want them to focus upon. Due to natural phenomenons like cloudiness in the area etc it becomes impossible for satellites to provide with any valuable data about the land on which it is focusing on .Hence it becomes important to classify the satellite images initially before sending them into further pipelines for processing. The core idea behind the work is to use a Deep Neural Network architecture and different Machine Learning Models which can find the inherent patterns in the images provided, based on the multiple labels assigned to the images and come up with a model which can give us the good accuracy for future years. The model can classify the images based on the multiple labels provided to it and after classification is done on multiple labels such as Farm, Forest, Urban, crop and can be selected later on as per the requirement of the desired area.

Sentinel-2 Bands	Central Wavelength (µm)	Resolution (m)
Band 1- Coastal aerosol	0.443	60
Band 2 - Blue	0.49	10
Band 3 - Green	0.56	10
Band 4 - Red	0.665	10
Band 5 - Vegetation Red Edge	0.705	20
Band 6 - Vegetation Red Edge	0.74	20
Band 7 - Vegetation Red Edge	0.783	20
Band 8 – NIR	0.842	10
Band 8A - Vegetation Red Edge	0.865	20
Band 9 - Water vapour	0.945	60
Band 1O - SWIR - Cirrus	1.375	60
Band 11 - SWIR	1.61	20
Band 12 - SWIR	2.19	20

Figure 2.1: Different bands of Sentinel L2A Satellite.

Many studies on Land and crop area classification have been done based on remote sensing and satellite image data. We have studied the approach of different researchers on satellite imagery classification. In one paper, researchers have classified land area using machine learning algorithm by taking NDVI as a feature and they have found among all machine learning algorithm random forest have performed well. Some have proposed a framework based on deep convolutions neural network (CNN) using Sentinel-2 time-series data sets to classify crops. By using this framework they saw that it has outperformed other state-of-the-art classification methods, including RF, XGBOOST, R-CNN, 2D-CNN, 3D-CNN. In other studies, some researchers took a single satellite image and wanted to classify crops in it to compare the accuracy of different machine learning and deep learning models. In further studies, researchers wants to see how much accuracy they can achieve by combining multi temporal and multi spectral data of sentinel 2 satellite image. They want to segment and detect the images received from satellites by using a deep learning system and image processing which classifies objects and facilities in high-resolution multi spectral satellite imagery.

In this study, our aim was to focus on satellite images and classifying them based on multiple classes such as Farms, Forests, Crops and Urban Areas. Two data-sets for the project were extracted from Sentinel Hub (open source for Satellite Image extraction) and Planet Scope. We have applied machine learning algorithms such as SVM, Random forest, XGboost, Gradient

Boosting, KNN and Deep Learning algorithm (CNN-1D) for crop, Farm, Forest, Urban area classification. Multiple experiments with different combinations of feature sets as different vegetation indices were carried out to build a better model. This study gave an inspiration in selecting targeted indexes and period of images for acquiring more accurate and timelier crop and land classification. The proposed method could be transferred to larger areas as well to see the different classification for better learning.

Chapter 3

Data-Set Description

3.1 Study Area

Area of study for this project was considered as Chhatbir, Punjab, India (Fig 3.1). The bounded box of which are given as: [76.77, 30.58, 76.81, 30.62.]. We extracted two data-sets for satellite imagery: 1. Sentinel Hub (open source) and 2. Planet Scope, which are the designer and builder of the world's largest constellation of Earth-imaging satellites. Extracted images of Sentinel-2 L2A satellite are of 10m spatial resolution and for Planet Scope 1.5m spatial resolution for the year 2018 to 2021. The extracted dataset had cloudy images which were removed by gdal using digital elevation model and colour relief techniques. Fig 3.2 depicts the multiple color coded images extracted from Sentinel Hub for the years 2018 to 2020.

Figure 3.1: Area of study: Chhatbir, Punjab, India. Bounded box coordinate of which are: 76.77, 30.58, 76.81, 30.62

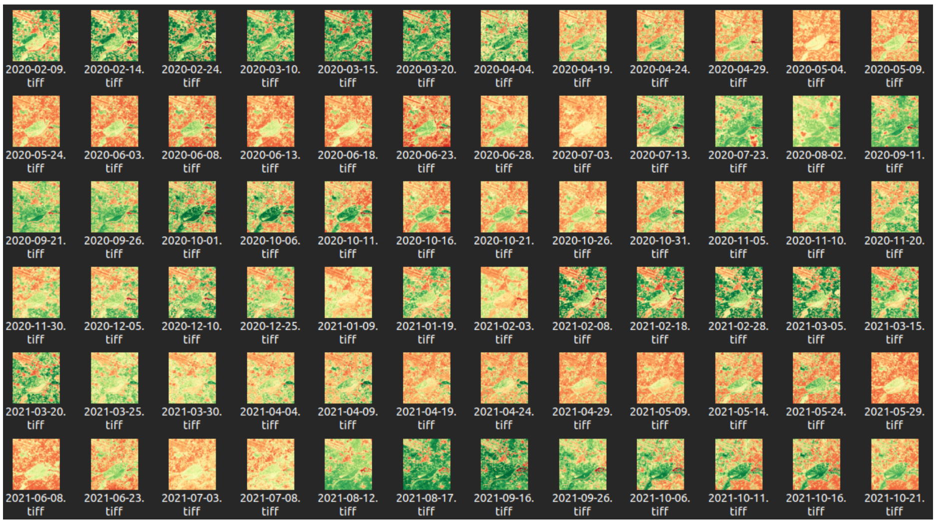

Figure 3.2: Multiple extracted images from the Sentinel L2A Satellite.

3.2 Ground Truth Data

For the ground truth data we have used Earth Explorer (open source software). We have around 2700 different tags for classes (Farm, Forest, Urban, Crop) for the same bounded box of Chhatbir, Punjab. Fig 3.3 depicts the tagged image with the color coded image for Chhatbir and Fig 3.4 shows the number counts for different classes.

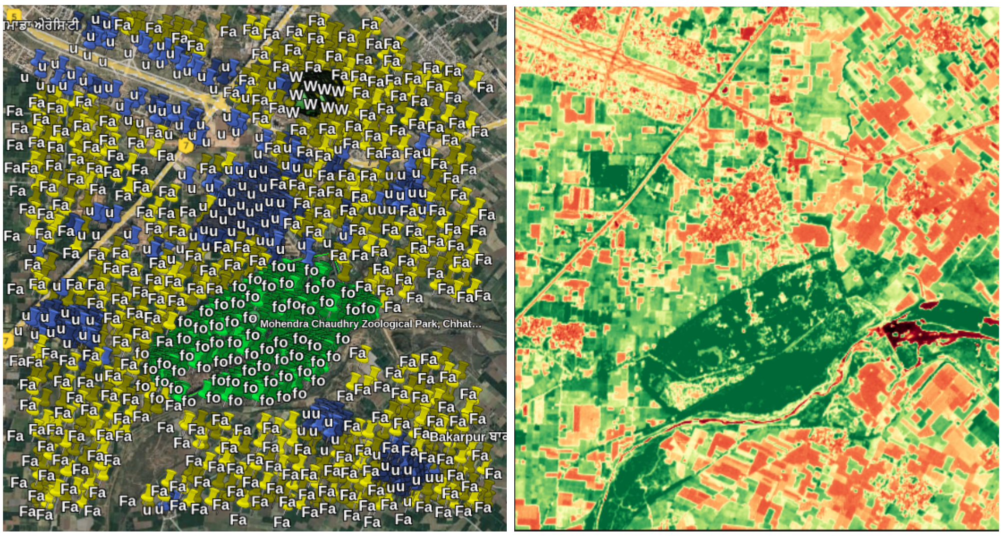

Figure 3.3: Chhatbir tagged classes image and the color coded image. Bounded box Coordinates are :76.77, 30.58, 76.81, 30.62

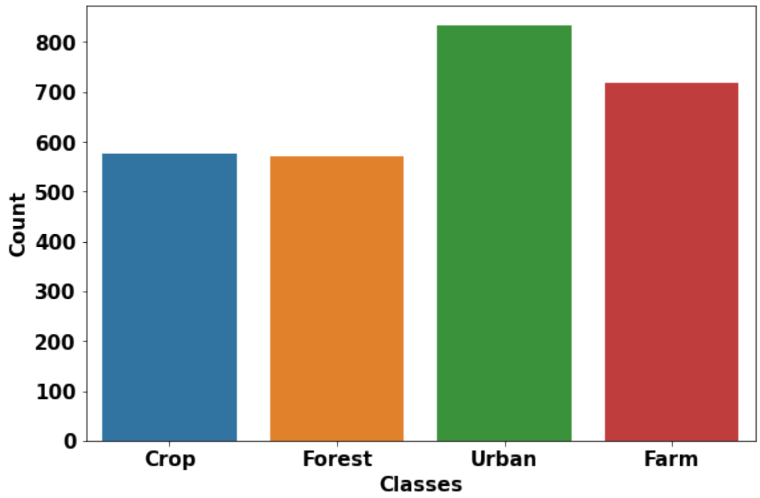

Figure 3.4: Count plot all the tagged classes (Farm, Forest, Urban, Crop)

3.3 Median Image Calculation

After collecting the Satellite Image data and Ground truth data, For a particular image we calculated different indices using different bands of Satellite. The formulae for all the indices are given in the Fig 3.5. For our analysis we took the median of all the images of a month and then finalise the single image for a particular month. So, we have 12 images data for all the calculated indices.

Name	*Formula*
ARI	$\frac{1.0}{B03} - \frac{1.0}{B05}$
ARVI	$\frac{B09 - B04 - y * (B04 - B02)}{B09 + B04 - y * (B04 - B02)}$
CHL-RED-EDGE	$\frac{B07^{-1}}{B05}$
EVI	$2{,}5 * \frac{B08 - B04}{B08 + 6 * B04 - 7.5 * B02 + 1}$
EVI2	$2{,}4 * \frac{B08 - B04}{B08 + B04 + 1{,}0}$
GNDVI	$\frac{B08 - B03}{B08 + B03}$
MCARI	$((B05 - B04) - 0.2 * (B05 - B03)) * \frac{B05}{B04}$
MSI	$\frac{B11}{B08}$
NBR	$\frac{B08 - B12}{B08 + B12}$
NDII	$\frac{B08 - B11}{B08 + B11}$
NDVI	$\frac{B08 - B04}{B08 + B04}$
NDWI	$\frac{B03 - B08}{B03 + B08}$
PSSR	$\frac{B08}{B04}$
SAVI	$\frac{B08 - B04}{B08 + B04 + L} * (1.0 + L)$
SIPI	$\frac{B08 - B01}{B08 - B04}$

Figure 3.5: Formulae for all the different indices using different bands of Sentinel 2A Satellite.

Fig 3.6 shows the data frame for two years 2020 and 2021 (24 images) with different columns and rows. Number of rows of the data are: 24 images * 2132 tagged pixels (Farm, Forest, Urban) per image (51168). Columns represents longitude, latitude, row of a image matrix, column of a image matrix, date, NDVI (Normalized Difference Vegetation Index), EVI (Enhanced Vegetation Index, EVI2, GNDVI (Green Normalized Vegetation Index), NDWI (Normalized Difference Water Index),and SAVI (Soil Advanced Vegetation Index) with the different classes.

	longitude	latitude	row	col	date	ndvi	evi	evi2	gndvi	ndwi	savi	classes
0	76.797543	30.604919	245	269	1-2020	0.772727	0.371904	0.354188	0.698452	-0.698452	0.392668	fo
1	76.792148	30.603033	194	290	1-2020	0.735824	0.247099	0.237075	0.687419	-0.687419	0.275246	fo
2	76.789126	30.603242	166	288	1-2020	0.647917	0.263014	0.250470	0.631579	-0.631579	0.286521	fo
3	76.799180	30.603627	260	284	1-2020	0.777778	0.397324	0.369260	0.721365	-0.721365	0.406004	fo
4	76.787589	30.601429	151	309	1-2020	0.603432	0.259065	0.251149	0.601688	-0.601688	0.283451	fo
...	...	...	...	...	...	...	...	...	...	...	...	...
51163	76.773528	30.594917	18	382	12-2021	0.539952	0.392841	0.320665	0.454969	-0.454969	0.336213	Fa
51164	76.771758	30.598198	2	345	12-2021	0.601985	0.493290	0.413931	0.529133	-0.529133	0.409417	Fa
51165	76.772659	30.607510	10	240	12-2021	0.647638	0.534437	0.449147	0.565583	-0.565583	0.450443	Fa
51166	76.772625	30.606585	10	251	12-2021	0.617809	0.493264	0.396070	0.521066	-0.521066	0.397562	Fa
51167	76.773583	30.605530	19	262	12-2021	0.570776	0.412723	0.338728	0.471763	-0.471763	0.353933	Fa

51168 rows × 12 columns

Figure 3.6: Data-frame table for all the indices for both the 2020 and 2021 year.

Chapter 4

Exploratory Data Analysis

To see how different indices time series look like and what is their range, we started exploratory data analysis with the time series of these indices. Fig 4.5 shows the behaviour of all the vegetation indices (NDVI, GNDVI, EVI, EVI2, NDWI, and SAVI). From the figure it is visible that the range of all the indices lies between -1 to 1. Except NDWI all others are in the healthy vegetation range (from 0.1 to 0.8).

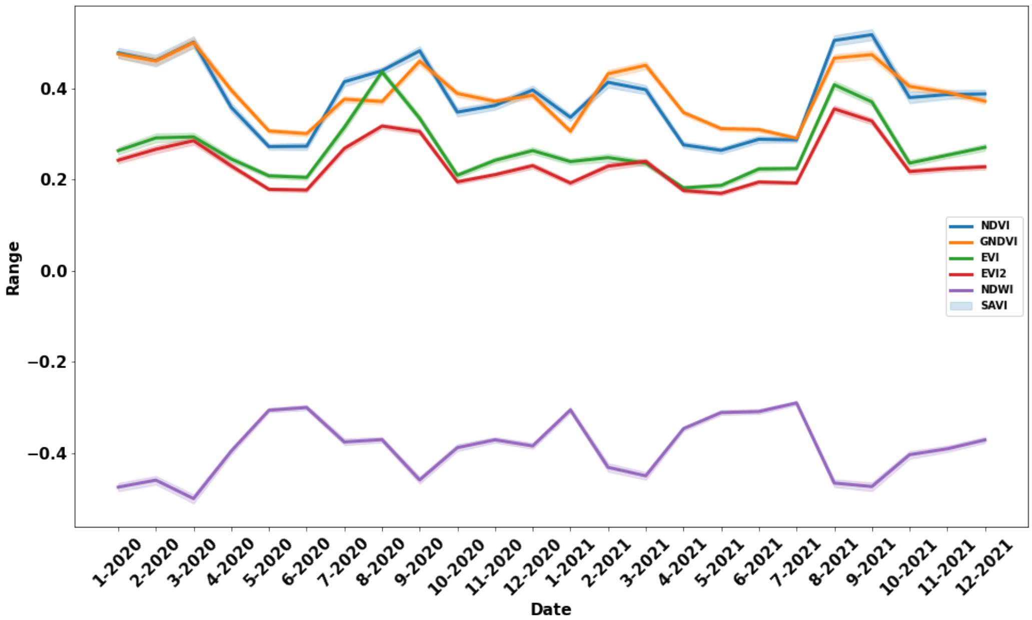

Figure 4.1: Time Series plot for all indices from Jan 2020 to December 2021.

Fig 4.2 presents the correlation matrix among all the indices. It shows that NDWI is highly anti-correlated among all the indices, and all other are highly correlated to each other.

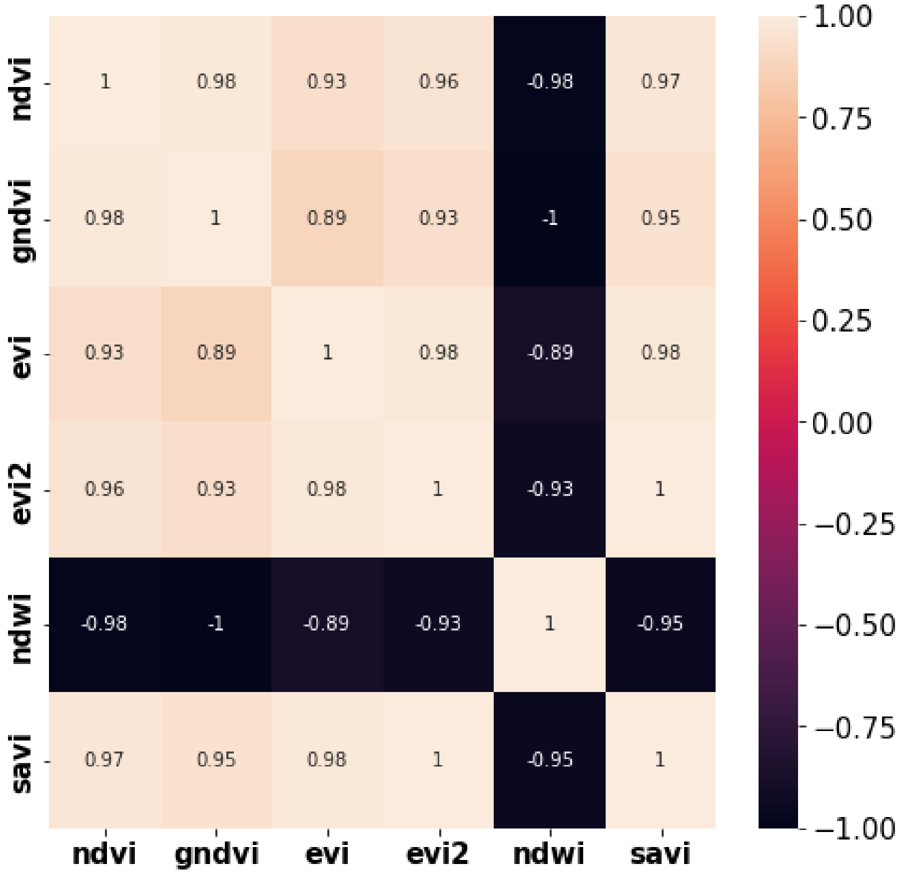

Figure 4.2: Cross-correlation Matrix for all the indices.

To see what distribution all the vegetation indices follows for different classes, we plot them all together in Fig 4.3. Figure shows that all the indices follows almost normal distribution (simple and mixture of normal distribution).

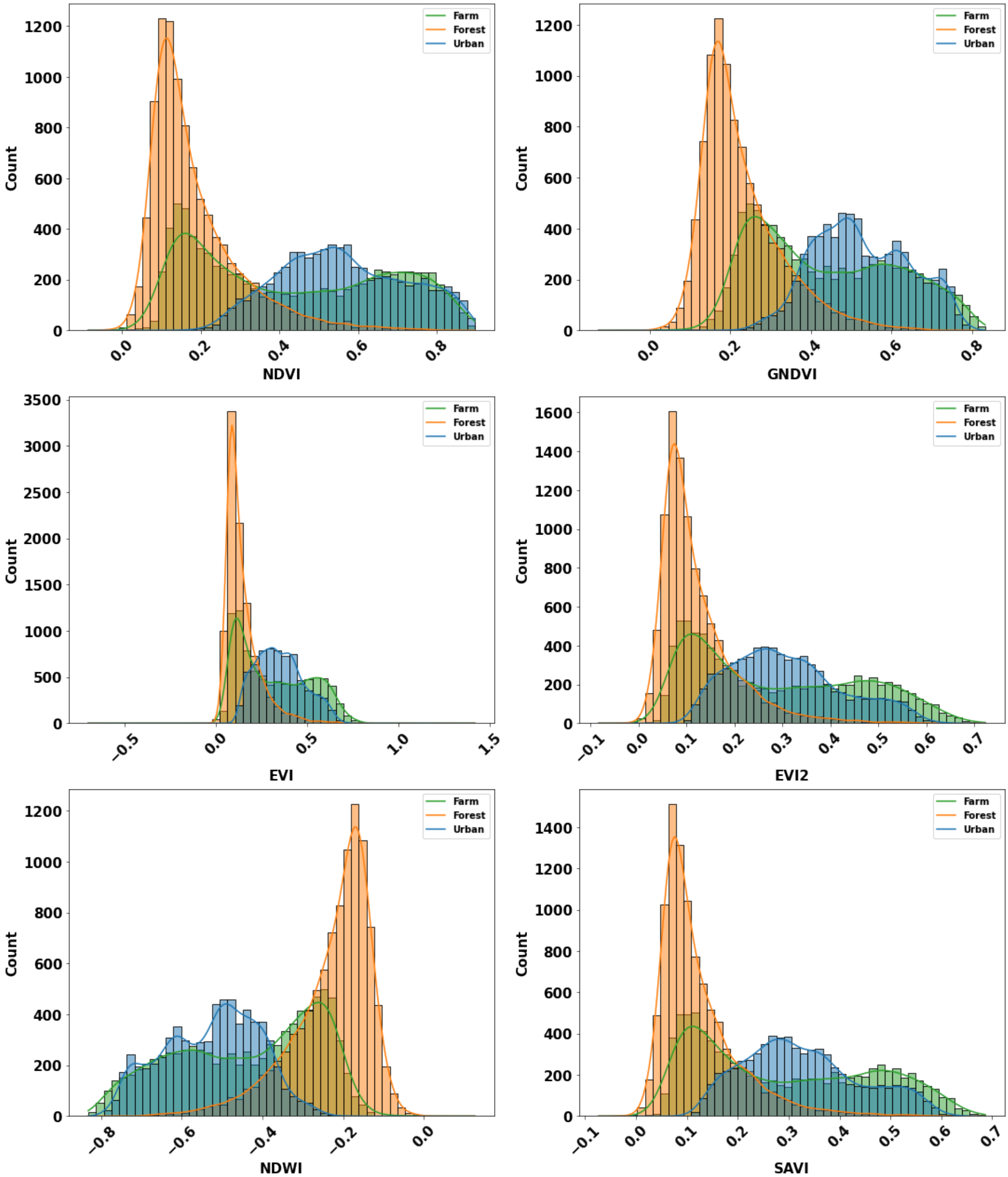

Figure 4.3: Distribution plot for all the indexes.

We plotted the Fig 4.4 to see if there are any outliers exits in our data set. We found that Urban class had many outliers, so we cleaned those from our data set.

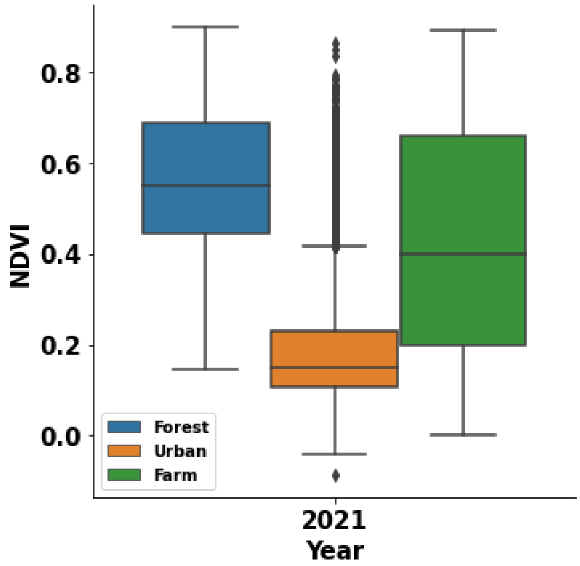

Figure 4.4: Box Plot for the Farm, Forest and Urban class for NDVI index

Fig 4.5 is the time series plot for all the classes for the year of 2021. We see the different behaviour for these classes. For crop it is clear from the time series that Chhatbir has two crop season. Farmers sow the Rice crop in June and the NDVI values are at it's peak in July, October and November and dips down when harvested in November/December, same is seen with the Wheat crop when sowed in December, it's values peak in January and February and dips down when harvested in March/April.

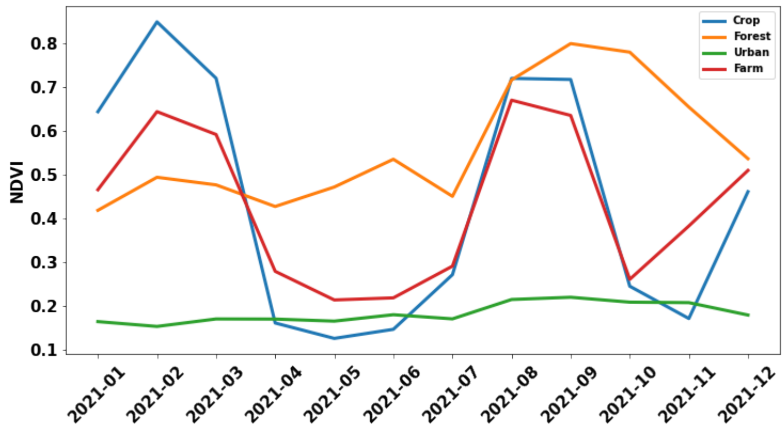

Figure 4.5: Time Series plot for all the classes for NDVI index.

We tried our hands on different combination of indices for all the classes for different time period. We found that NDVI was performing best among all. In the following methodology section we have explained the whole pipeline and workflow of this study.

Chapter 5

Methodology

A variety of Machine learning Algorithms were explored, including support vector machines (SVMs), K-Nearest Neighbors (KNN), GRADIENT BOOST, XGBoost, Random Forest and a Convolutional Neural Network (CNN 1D).

Fig 5.1 is the methodology flow. First, the data was extracted from sentinel hub platform. Second, the data was manually tagged to represent ground truth. Third, many pre-processing techniques were used to clean and mold the data. Fourth, EDA was done to remove outliers and check the integrity of the data. Fifth, Machine Learning and Deep Learning models were implemented and lastly a final/predicted image was created.

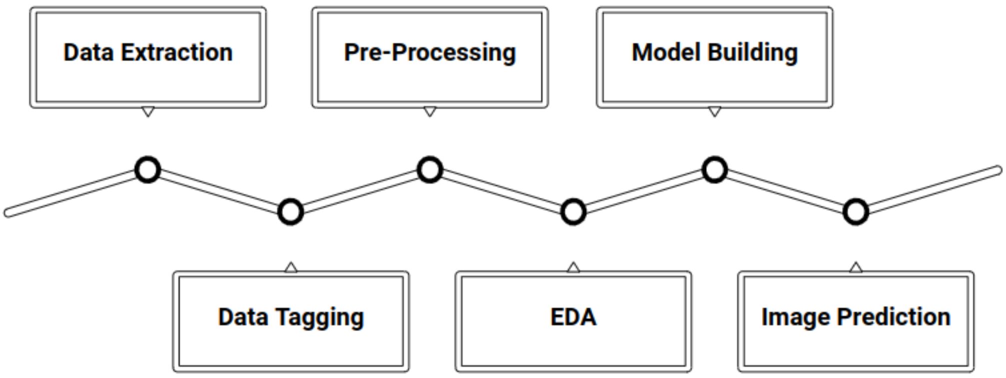

Figure 5.1: Flowchart for the proposed methodology.

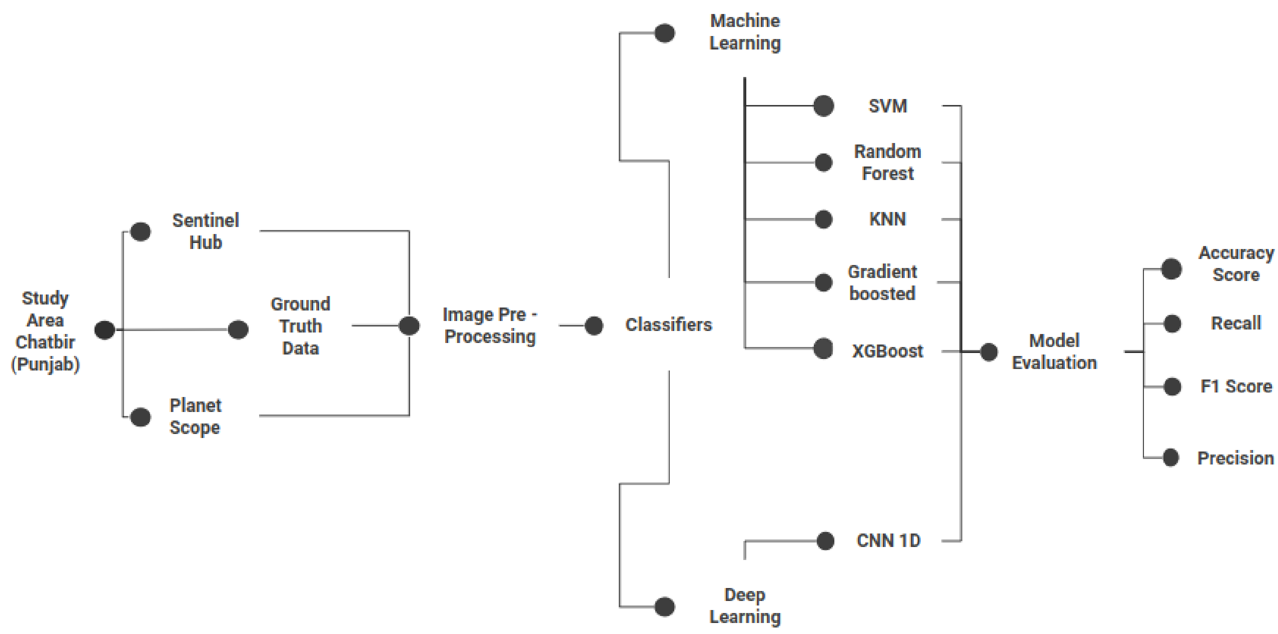

Figure 5.2: Pipeline of the project.

Fig 5.2 is the detailed workflow for this study.

First, an API was created to extract images from Sentinel hub which was built on top of the Sentinel Hub package[1]. the API requires the target bounding box, start, end date and the login credentials acquired from sentinel hub. Since the time interval between each image of sentinel hub is 5 days the output from the API are 4-5 images per month. Images extracted from the API were color coded using digital elevation and color relief techniques to better visualise cloudy images. Second, the area was tagged with labels (Farm, Forest, Urban and Crop) using Google Earth Engine to represent ground truth and only the tagged pixels were collected using the GDAL package [2] using Inverse Geo Transform. Third, in Image pre-processing a single median image was created for a particular month from all available non-cloudy images (typically 3-4). A final dataset was created using months as features and the labels as our dependent variable. Different Machine Learning Algorithms and a Deep Learning CNN-1D model was created and evaluated over different metrics F1 Score, Precision, Recall and Accuracy Score.

5.1 Machine Learning Models

5.1.1 SVM

The objective of SVM algorithm is to find a hyperplane in an N-dimensional space that distinctly classifies the data points. An SVM classifies data by finding the best hyperplane that separates all data points of one class from those of the other class. The best hyperplane for an SVM means the one with the largest margin between the two classes. Margin means the maximal width of the slab parallel to the hyperplane that has no interior data points.

5.1.2 KNN

K-Nearest Neighbors algorithm, also known as KNN , is a non-parametric, supervised learning classifier, which uses proximity to make classifications or predictions about the grouping of an individual data point. While it can be used for either regression or classification problems, it is typically used as a classification algorithm, working off the assumption that similar points can be found near one another.

5.1.3 RANDOM FOREST

Every decision tree has high variance, but when we combine all of them together in parallel then the resultant variance is low as each decision tree gets perfectly trained on that particular sample data and hence the output doesn't depend on one decision tree but multiple decision trees. In the case of a classification problem, the final output is taken by using the majority voting classifier. In the case of a regression problem, the final output is the mean of all the outputs. This part is Aggregation. The basic idea behind this is to combine multiple decision trees in determining the final output rather than relying on individual decision trees. Random Forest has multiple decision trees as base learning models.

5.1.4 GRADIENT BOOST

It is a technique of producing an additive predictive model by combining various weak predictors, typically Decision Trees. Gradient Boosting Trees can be used for both regression and classification.

5.1.5 XGBoost

XGBoost stands for Extreme Gradient Boosting. XGBoost is an implementation of Gradient Boosted decision trees. In this algorithm, decision trees are created in sequential form. Weights play an important role in XGBoost. Weights are assigned to all the independent variables which are then fed into the decision tree which predicts results. The weight of variables predicted wrong by the tree is increased and these variables are then fed to the second decision tree. These individual classifiers/predictors then ensemble to give a strong and more precise model. It can work on regression, classification, ranking, and user-defined prediction problems.

5.2 Deep Learning Model

5.2.1 CNN 1D Architecture

Fig 5.3 is the brief description about our CNN 1d architecture. Here, input shape is(12,1) where, 12 is the number of features (12 months) Then we passed it through convolution 1d layer with 64 filters and 3 filter size with zero padding and stride 1. After convolution layer we used batch normalization so that we can keep the distribution same in next input layer and finally we passed it through ReLU activation function and again we followed the same process as you can see the below figure . At the end we used global average pooling layer instead of fully connected layer to reduce the dimensionality and reduce the number of parameters also. followed by the soft max layer as we have multi classes in our train data set. Here we have used Adam optimizer and categorical cross entropy as a cost function.

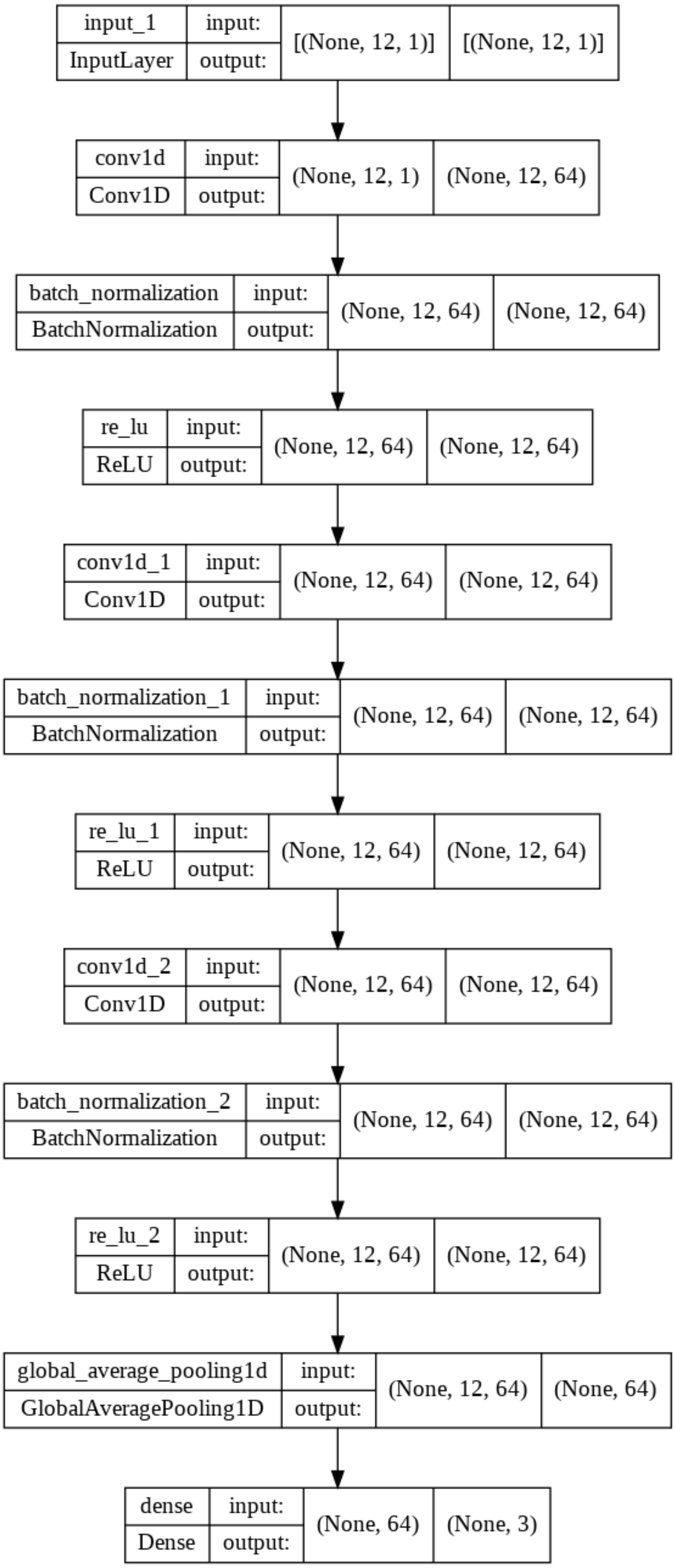

Figure 5.3: Complete model architecture for CNN 1D

Chapter 6

Results

Quantitative results for each of the Machine learning methods are outlined in Tables 1 - 3, see Fig (6.1,6.3,6.2). Tables 1 and 3 show the results of the multi models for both the Sentinel Hub and Planet Scope data, respectively. A comparison between indicates that all models had higher prediction accuracy on the different time period data-set, as expected. But results for temporal analysis can not be seen using these Machine learning models. This provides an important insight that temporal information could be helpful for crop classification, showing that crops have distinguishable temporal signatures throughout the crop cycle. We switched to Deep Learning Models and found some interesting results.

6.1 Machine Learning

Trained over 2018						Tested over 2019		Tested over 2020		Tested over 2021	
Algorithms	**Labels**	**Precision**	**Recall**	**F1 score**	**Accuracy Score**	**F1 Score**	**Accuracy Score**	**F1 Score**	**Accuracy Score**	**F1 Score**	**Accuracy Score**
	Farm	0.84	0.96	0.90		0.81		0.68		0.56	
SVM	Forest	0.97	0.84	0.90	0.91	0.89	0.90	0.90	0.85	0.83	0.81
	Urban	0.95	0.93	0.94		0.98		0.89		0.90	
	Farm	0.93	0.94	0.93		0.70		0.75		0.74	
XGBoost	Forest	0.97	0.96	0.96	0.95	0.21	0.72	0.20	0.73	0.14	0.71
	Urban	0.96	0.95	0.95		0.93		0.98		0.96	
	Farm	0.94	0.94	0.94		0.67		0.67		0.99	
Random Forest	Forest	0.97	0.98	0.97	0.95	0.14	0.67	0.07	0.69	0.81	0.81
	Urban	0.96	0.95	0.95		0.84		0.94		0.51	
	Farm	0.98	0.86	0.91		0.26		0.73		0.73	
Gradient Boosted	Forest	0.93	0.98	0.96	0.93	0.62	0.47	0.95	0.69	0.94	0.68
	Urban	0.90	0.96	0.93		0.03		0.08		0.03	
	Farm	0.90	0.92	0.91		0.36		0.86		0.85	
KNN	Forest	0.85	0.78	0.86	0.89	0.78	0.76	0.82	0.82	0.87	0.88
	Urban	0.85	0.94	0.89		0.98		0.78		0.93	

Figure 6.1: Machine Learning algorithms result for Farm, Forest and Urban

Fig 6.1 shows the results of different Machine Learning Algorithms for classes Farm, Forest and Urban. All the different models were trained over 2018 data and tested over 2019, 2020 and 2021. It is clearly seen in the table that tree based Algorithms (XGBoost, Random Forest and Gradient Boosting) are overfitting and performing poorly on the test/unseen data. SVM and KNN Algorithms are performing better and consistent through out the years.

Trained over 2018						Tested over 2019		Tested over 2020		Tested over 2021	
Algorithms	Labels	Precision	Recall	F1 score	Accuracy Score	F1 Score	Accuracy Score	F1 Score	Accuracy Score	F1 Score	Accuracy Score
	Forest	0.90	0.59	0.71		0.65		0.86		0.81	
SVM	Urban	0.74	0.95	0.83	0.84	0.85	0.85	0.82	0.82	0.99	0.81
	Wheat	1.00	0.92	0.95		0.99		0.78		0.51	
	Forest	0.98	0.98	0.98		0.20		0.26		0.36	
XGBoost	Urban	0.92	0.99	0.95	0.96	0.75	0.73	0.65	0.63	0.75	0.75
	Wheat	1.00	0.90	0.95		0.98		0.70		0.98	
	Forest	0.97	0.98	0.98		0.73		0.29		0.23	
Random Forest	Urban	0.98	0.98	0.98	0.98	0.65	0.72	0.73	0.73	0.63	0.68
	Wheat	1.00	0.99	1.00		0.96		0.96		0.88	
	Forest	0.94	0.86	0.90		0.96		0.95		0.94	
Gradient Boosted	Urban	0.90	0.96	0.93	0.94	0.74	0.71	0.73	0.67	0.73	0.70
	Wheat	1.00	0.98	0.99		0.14		0.20		0.30	
	Forest	0.96	0.60	0.74		0.90		0.78		0.83	
KNN	Urban	0.77	0.98	0.86	0.87	0.81	0.88	0.76	0.77	0.87	0.83
	Wheat	1.00	0.97	0.99		0.70		0.80		0.78	

Figure 6.2: Machine Learning algorithms result for Wheat, Forest and Urban

Same methodology was used for crop classification, We dropped the Farm Values from the dataset and replaced 'crop' tag with 'wheat' tag. Fig 6.2 shows the results of classes Wheat, Forest and Urban. Number of features vary here as wheat is a seasonal crop. So, the features/months used were October-April (7 months).

Trained over 2018						Tested over 2019		Tested over 2020		Tested over 2021	
Algorithms	Labels	Precision	Recall	F1 score	Accuracy Score	F1 Score	Accuracy Score	F1 Score	Accuracy Score	F1 Score	Accuracy Score
	Forest	0.99	0.93	0.96		0.82		0.83		0.76	
SVM	Rice	0.95	0.86	0.90	0.92	0.86	0.87	0.86	0.87	0.81	0.83
	Urban	0.87	0.97	0.91		0.91		0.92		0.90	
	Forest	0.99	0.90	0.94		0.11		0.57		0.69	
XGBoost	Rice	0.97	0.91	0.94	0.93	0.69	0.69	0.70	0.71	0.76	0.76
	Urban	0.88	0.97	0.93		0.89		0.78		0.80	
	Forest	0.99	0.94	0.96		0.41		0.19		0.63	
Random Forest	Rice	0.97	0.99	0.98	0.97	0.74	0.76	0.72	0.75	0.69	0.72
	Urban	0.95	0.97	0.96		0.93		0.87		0.81	
	Forest	0.99	0.90	0.95		0.22		0.48		0.77	
Gradient Boosted	Rice	0.98	0.99	0.99	0.96	0.71	0.73	0.75	0.78	0.64	0.70
	Urban	0.93	0.98	0.96		0.95		0.98		0.69	
	Forest	0.99	0.93	0.96		0.59		0.78		0.73	
KNN	Rice	0.98	0.82	0.89	0.92	0.77	0.80	0.84	0.87	0.81	0.84
	Urban	0.85	0.98	0.91		0.94		0.95		0.94	

Figure 6.3: Machine Learning algorithms result for Rice, Forest and Urban

Fig 6.3 represents the results for rice crop classification. Features/Months were used June-October (5 Months). After trying different Machine Learning Algorithms, It was concluded that Machine Learning Algorithms have difficulty in creating a generalised model and since our data is temporal, we tried Deep Learning CNN-1D architecture.

6.2 CNN 1D

Fig 6.4 shows the results of CNN-1D Model for classes Farm, Forest and Urban. The model is showing consistent, high accuracy scores when tested over different years.

		Farm, Forest and Urban			Wheat, Forest and Urban			Rice, Forest and Urban		
Trained over 2020	Labels	Farm	Forest	Urban	Wheat	Forest	Urban	Rice	Forest	Urban
	Precision	0.94	0.98	0.90	0.93	0.97	0.96	0.99	0.99	0.99
	Recall	0.89	0.95	0.96	0.94	0.96	0.95	0.99	1.00	0.99
	F1 score	0.92	0.97	0.93	0.93	0.96	0.95	0.99	1.00	0.99
	Accuracy Score	0.96			0.95			0.99		
Tested over 2018	F1 Score	0.97	0.82	0.88	0.89	0.92	0.89	0.87	0.82	0.95
	Accuracy Score	**0.89**			**0.90**			**0.88**		
Tested over 2019	F1 Score	0.95	0.97	0.95	0.97	0.94	0.95	0.96	0.94	0.93
	Accuracy Score	**0.95**			**0.95**			**0.94**		
Tested over 2021	F1 Score	0.92	0.96	0.92	0.94	0.99	0.95	0.93	0.92	0.96
	Accuracy Score	**0.93**			**0.95**			**0.94**		

Figure 6.4: CNN 1D model result for all the considered classes for Test years: 2018, 2019, 2021 year. Trained year: 2020

```
testing accuracy:  0.9607535321821036

Predicted  Farm  Forest  Urban
Actual
Farm        189       4     12
Forest        1     187      1
Urban         7       0    236

              precision    recall  f1-score   support

        Farm       0.96      0.92      0.94       205
      Forest       0.98      0.99      0.98       189
       Urban       0.95      0.97      0.96       243

    accuracy                           0.96       637
   macro avg       0.96      0.96      0.96       637
weighted avg       0.96      0.96      0.96       637
```

```
testing accuracy:  0.9737654320987654

Predicted  Farm  Forest  Urban
Actual
Farm        209       4      2
Forest        1     183      2
Urban         8       0    239

              precision    recall  f1-score   support

        Farm       0.96      0.97      0.97       215
      Forest       0.98      0.98      0.98       186
       Urban       0.98      0.97      0.98       247

    accuracy                           0.97       648
   macro avg       0.97      0.97      0.97       648
weighted avg       0.97      0.97      0.97       648
```

Figure 6.5: CNN 1D result for Sentinel 2A and Planet scope Image for year 2021

CNN-1D Model trained on Sentinel Hub was compared with Model trained on Planet Scope data to check whether high resolution images will improve the overall accuracy or not. The Planet Scope model is able to predict classes with higher accuracy, Fig 6.5 misclassification has also been reduced (17 out of 648), where as Sentinel Hub data shows misclassification (25 out of 648).

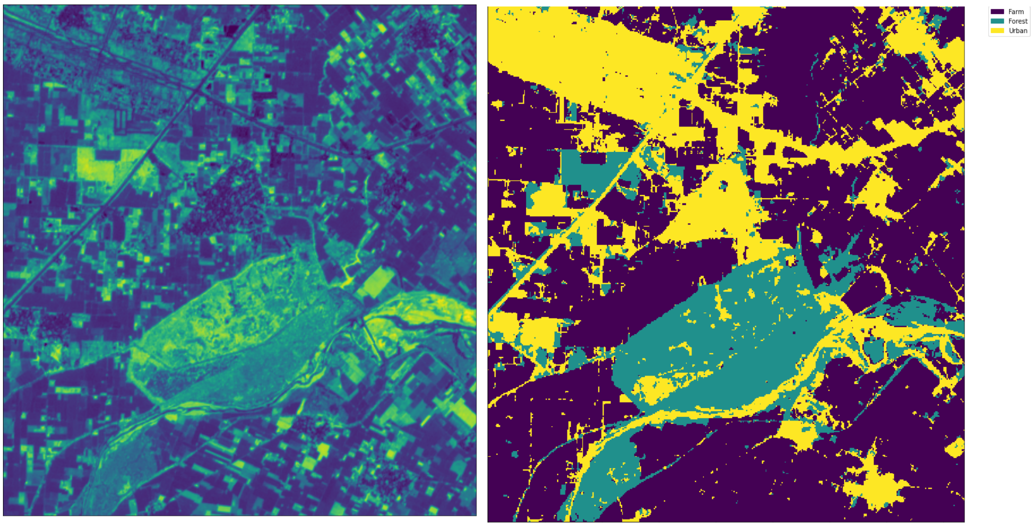

Figure 6.6: Spatial visualisation of actual vs predicted image for April 2021

A final predicted image Fig 6.6 was created using the proposed CNN-1D model to predict every pixel (1,89,807) of original sentinel image not only the tagged but also untagged pixels. The model is able to predict unseen data very clearly like the roads, streets, pathways and villages/towns as urban. It has also classified Farms and Forest at a pixel level.

Chapter 7

Conclusion and Future Scope

7.1 Conclusion

We Started with extracting Satellite images from open source (Sentinel Hub) and used Earth Explorer software to tag/label the data and then color coded the images using Gdal and Qgis to detect cloud images and then cleaned the data by manually removing cloudy images. NDVI performed best among all the indices that we have calculated using different bands of satellite data. We applied Machine learning and deep learning algorithms to test over multiple years and results showed that CNN 1D algorithm among all is giving the best accuracy for different years. To see the Comparison between different datasets (Sentinel Hub and Planet Scope), we used the proposed CNN-1D model to train and test over different years for classes (Farm, Forest and Urban) and found that planet scope data is giving us low misclassification and higher accuracy scores than sentinel hub, because planet scope has higher (1.5m spatial resolution) compared to sentinel hub.

7.2 Future Scope

We have used Chhatbir, Punjab area for this study. We want to test and generalise the best model for larger area and want to extend the classification for different crops. Our main focus would be on finalizing the package for Sentinel Hub API and creating a complete pipeline and make it public so that researchers can extract the data on their own for their interested area of study.

Bibliography

[1] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," vol. 25, 2012. [Online]. Available:https://proceedings.neurips.cc/paper/2012/file/c399862d3b9d6b76c8436e924a68c45b-Paper.pdf

[2] K. Simonyan and A. Zisserman, "Very deep convolutional networks for largescale image recognition," CoRR, vol. abs/1409.1556, 2014. [Online]. Available: http://arxiv.org/abs/1409.1556

[3] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. E. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich, "Going deeper with convolutions," CoRR, vol. abs/1409.4842, 2014. [Online]. Available: http://arxiv.org/abs/1409.4842

[4] S. Ioffe and C. Szegedy, "Batch normalization: Accelerating deep network training by reducing internal covariate shift," CoRR, vol. abs/1502.03167, 2015. [Online]. Available: http://arxiv.org/abs/1502.03167

[5] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," CoRR, vol. abs/1512.03385, 2015. [Online]. Available: http://arxiv.org/abs/1512.03385

[6] M. Tan and Q. V. Le, "Efficientnet: Rethinking model scaling for convolutional neural networks," CoRR, vol. abs/1905.11946, 2019. [Online]. Available: http://arxiv.org/abs/1905.11946

[7] A. Paszke, S. Gross, F. Massa, A. Lerer, J. Bradbury, G. Chanan, T. Killeen, Z. Lin, N. Gimelshein, L. Antiga, A. Desmaison, A. K¨opf, E. Z. Yang, Z. DeVito, M. Raison, A. Tejani, S. Chilamkurthy, B. Steiner, L. Fang, J. Bai, and S. Chintala, "Pytorch: An imperative style, high-performance deep learning library," CoRR, vol. abs/1912.01703, 2019. [Online]. Available: http://arxiv.org/abs/1912.01703

[8] J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, and L. Fei-Fei, “Imagenet: A large-scale hierarchical image database,” pp. 248–255, 2009.

[9] D. P. Kingma and J. Ba, “Adam: A method for stochastic optimization,” 2014, cite arxiv:1412.6980Comment: Published as a conference paper at the 3rd International Conference for Learning Representations, San Diego, 2015. [Online]. Available: http://arxiv.org/abs/1412.6980

[10] Pan, Yude & Birdsey, Richard & Fang, Jingyun & Houghton, Richard & Kauppi, Pekka & Kurz, Werner & Phillips, Oliver & Shvidenko, Anatoly & Lewis, Simon & Canadell, Josep & Ciais, Philippe & Jackson, Robert & Pacala, Stephen & McGuire, A & Piao, Shilong & Rautiainen, Aapo & Sitch, Stephen & Hayes, Daniel. (2011). A Large and Persistent Carbon Sink in the World’s Forests. Science (New York, N.Y.). 333. 988-93. 10.1126/science.1201609.

[11] Ghosh, Sujit & Behera, Mukunda & Paramanik, Somnath. (2020). Canopy Height Estimation Using Sentinel Series Images through Machine Learning Models in a Mangrove Forest. Remote Sensing. 12. 1519. 10.3390/rs12091519.

[12] Lee, Won-Jin & Lee, Chang-Wook. (2018). Forest Canopy Height Estimation Using Multiplatform Remote Sensing Dataset. Journal of Sensors. 2018. 1-9. 10.1155/2018/1593129.

[13] García, Mariano & Saatchi, Sassan & Ustin, Susan & Balzter, Heiko. (2018). Modelling forest canopy height by integrating airborne LiDAR samples with satellite Radar and multispectral imagery. International Journal of Applied Earth Observation and Geoinformation. 66. 10.1016/j.jag.2017.11.017.

[14] Civco, D.L. Artificial neural networks for land-cover classification and mapping. Int. J. Geogr. Inf. Sci. 1993, 7, 173–186.

[15] Yang, C.; Wu, G.; Ding, K.; Shi, T.; Li, Q.; Wang, J. Improving land use/land cover classification by integrating pixel unmixing and decision tree methods. Remote Sens. 2017, 9, 1222

[16] Atkinson, P.M.; Tatnall, A.R. Introduction neural networks in remote sensing. Int. J. Remote Sens. 1997, 18, 699–709.

[17] Lu, D.; Weng, Q. A survey of image classification methods and techniques for improving classification performance. Int. J. Remote Sens. 2007, 28, 823–870.

[18] Dixon, B.; Candade, N. Multispectral landuse classification using neural networks and support vector machines: One or the other, or both? Int. J. Remote Sens. 2008, 29, 1185–1206

[19] Shafizadeh-Moghadam, H.; Hagenauer, J.; Farajzadeh, M.; Helbich, M. Performance analysis of radial basis function networks and multi-layer perceptron networks in modelling urban change: A case study. Int. J. Geogr. Inf. Sci. 2015, 29, 606–623

[20] Mannan, B.; Roy, J.; Ray, A.K. Fuzzy ARTMAP supervised classification of multi-spectral remotely-sensed images. Int. J. Remote Sens. 1998, 19, 767–774.

[21] Rahman, A.; Kumar, S.; Fazal, S.; Siddiqui, M.A. Assessment of land use/land cover change in the North-West District of Delhi using remote sensing and GIS techniques. J

[22] Chen, Z.; Wang, J. Land use and land cover change detection using satellite remote sensing techniques in themountainous Three Gorges Area, China. Int. J. Remote Sens. 2010, 31, 1519–1542. [CrossRef]