Object Detection and Classification Using Satellite Imagery

SABUDH

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Date: 21st June, 2022

Acknowledgement

- Mentors: Dr. Sukhjit Singh and Mr. Vijay Garg
- Mr. Vishal Dafada
- Entire Sabudh Team (Teaching and Non-Teaching)
- Fellow Interns

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- Methodology / Models
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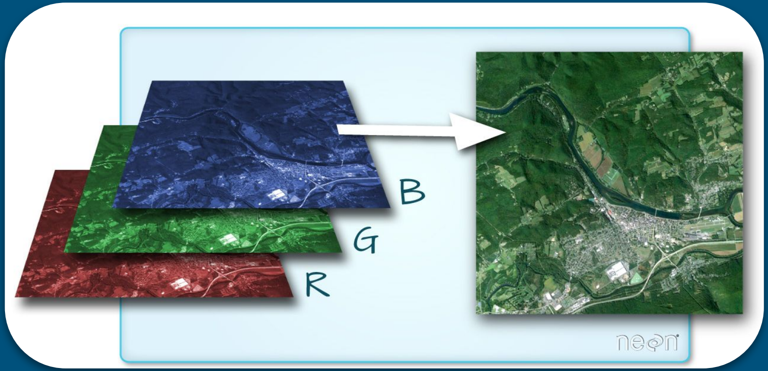
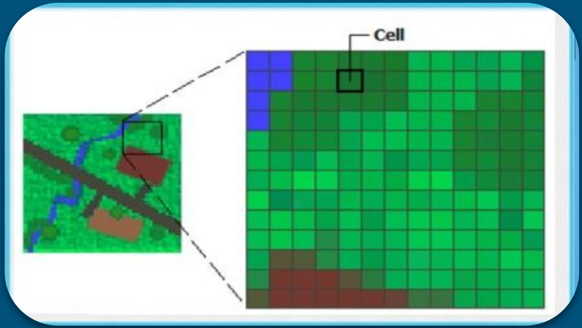
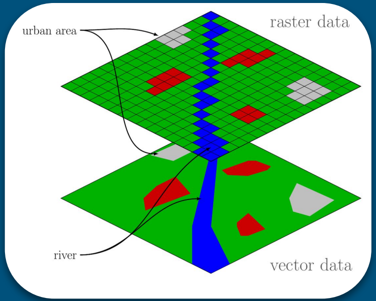
Introduction

- Transforming Energy into images
- Satellite images are images of earth collected by imaging satellites.
- Satellites have ability to collect more data, more quickly, than instruments on the ground.
- Different objects absorb or reflect different wavelengths of light.
- **Spatial resolution**
- **Spectral resolution**
- **Temporal resolution**
- **Radiometric resolution**



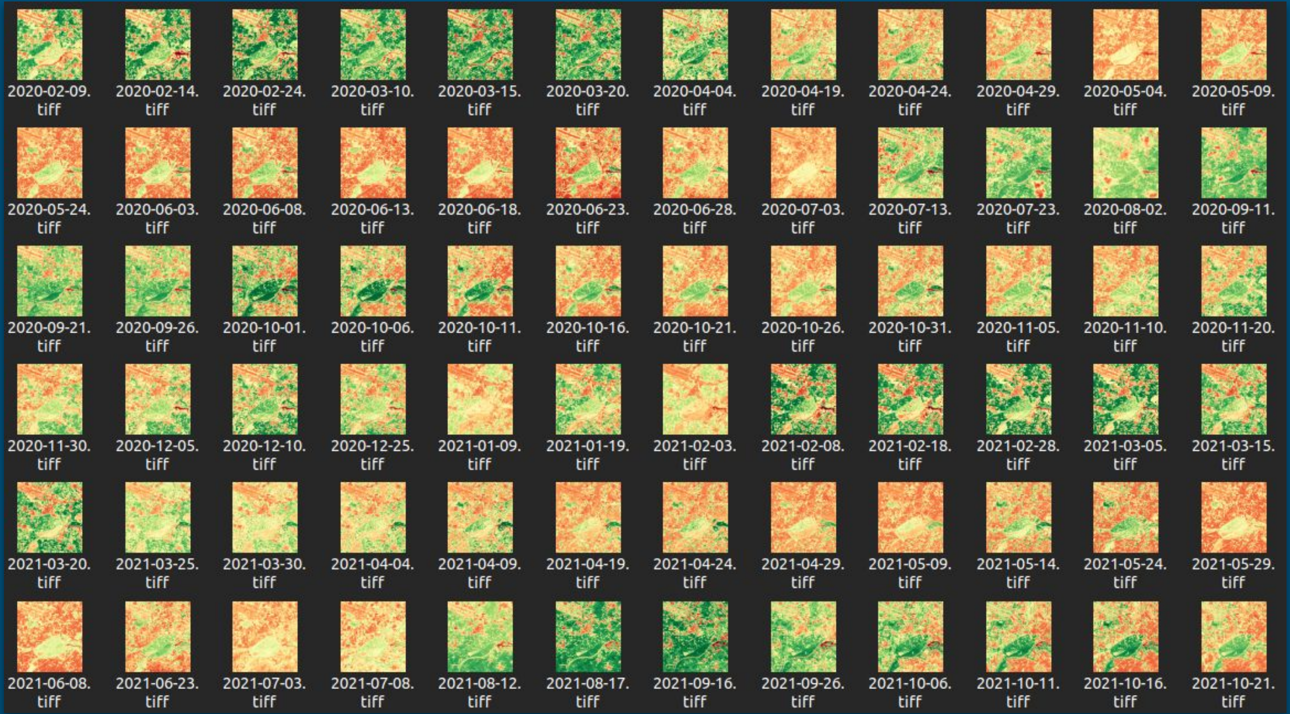


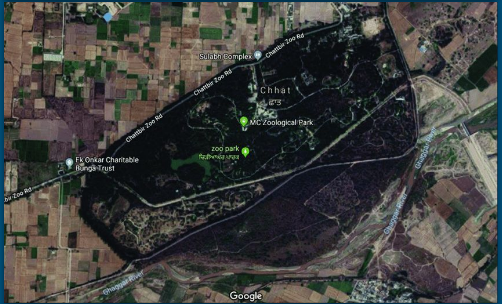


https://apps.sentinel-hub.com/dashboard/#/

Data Set Description

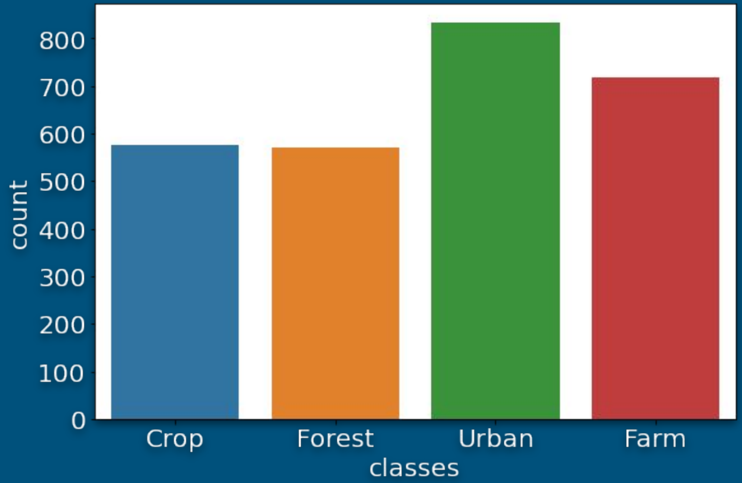
1. Image Extraction - Sentinel Hub





2. Data Tagging/labelling

Chatbir Bounding box Coordinates
[76.77, 30.58, 76.81, 30.62]



3. Different Indices Calculation

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	$\frac{B08 - B01}{B08 - B04}$

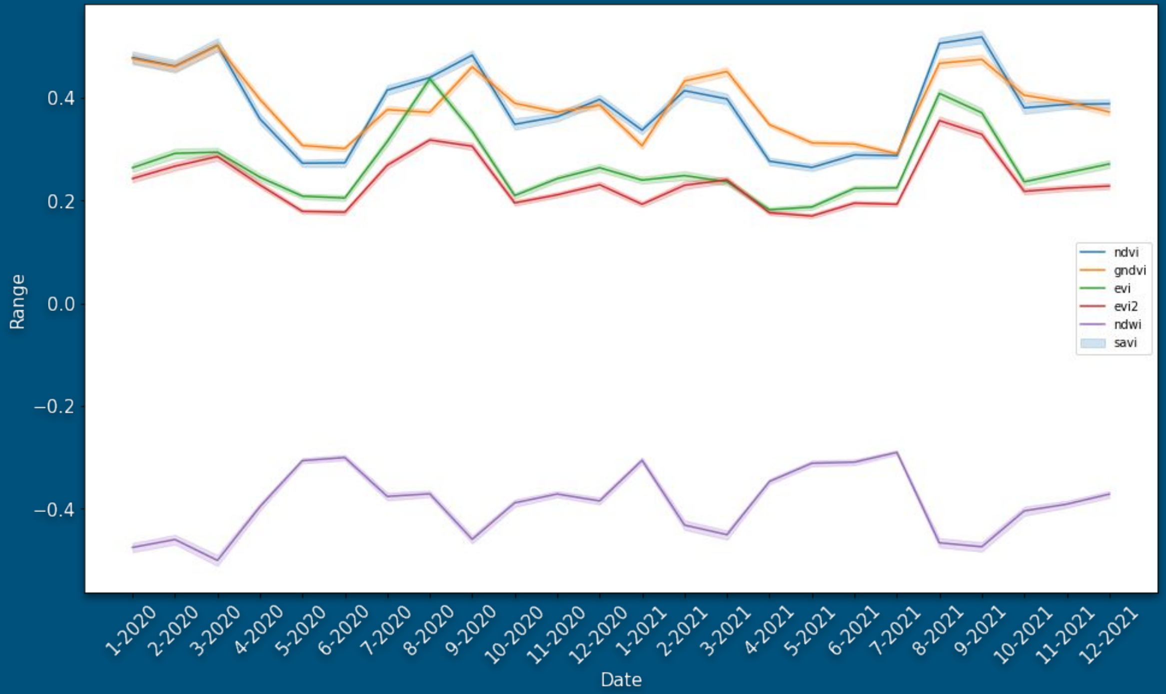
$$NDVI = \frac{NIR - Red}{NIR + Red}$$

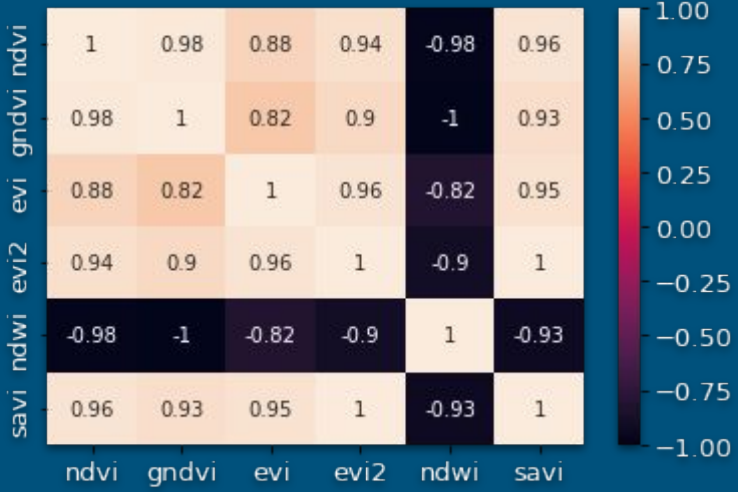
Sentinel-2 Bands	Central Wavelength (µm)	Resolution (m)
Band 1- Coastal aerosol	0.443	60
Band 2 - Blue	0.49	10
Band 3 - Green	0.56	10
Band 4 - Red	0.665	10
Band 5 - Vegetation Red Edge	0.705	20
Band 6 - Vegetation Red Edge	0.74	20
Band 7 - Vegetation Red Edge	0.783	20
Band 8 – NIR	0.842	10
Band 8A - 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

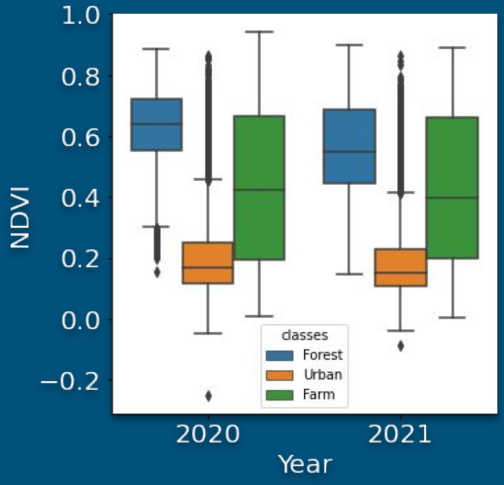
	longitude	latitude	row	col	date	ndvi	evi	evi2	gndvi	ndwi	savi	classes
0	76.797543	30.604919	245	269	1-2020	0.772727	0.371904	0.354188	0.698452	-0.698452	0.392668	fo
1	76.792148	30.603033	194	290	1-2020	0.735824	0.247099	0.237075	0.687419	-0.687419	0.275246	fo
2	76.789126	30.603242	166	288	1-2020	0.647917	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

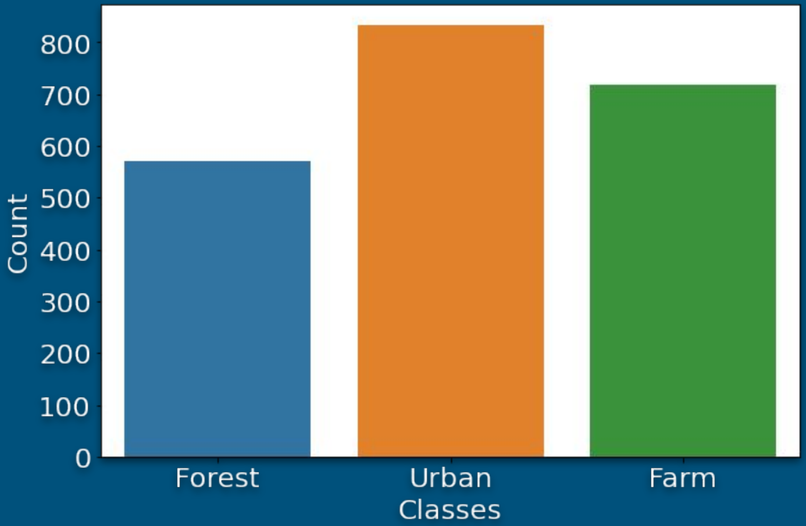
51168 rows × 12 columns

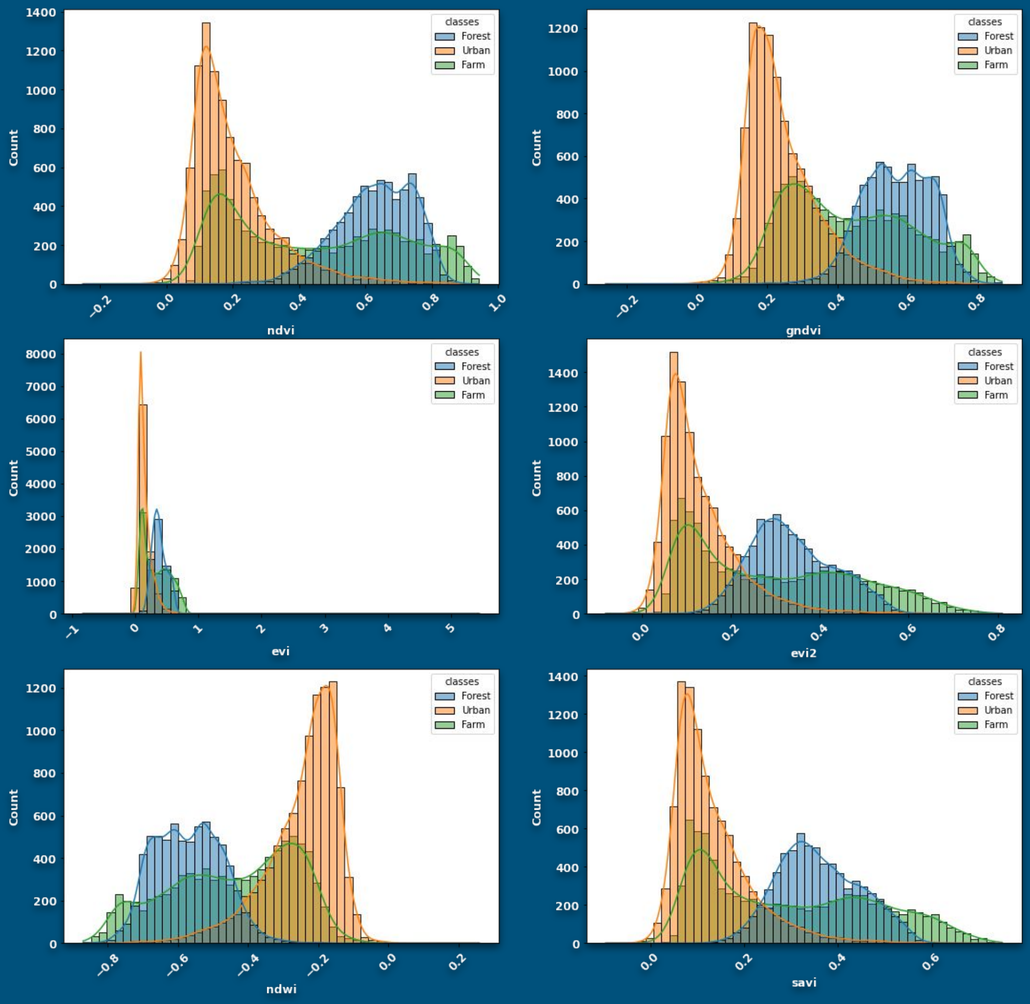
Exploratory Data Analysis



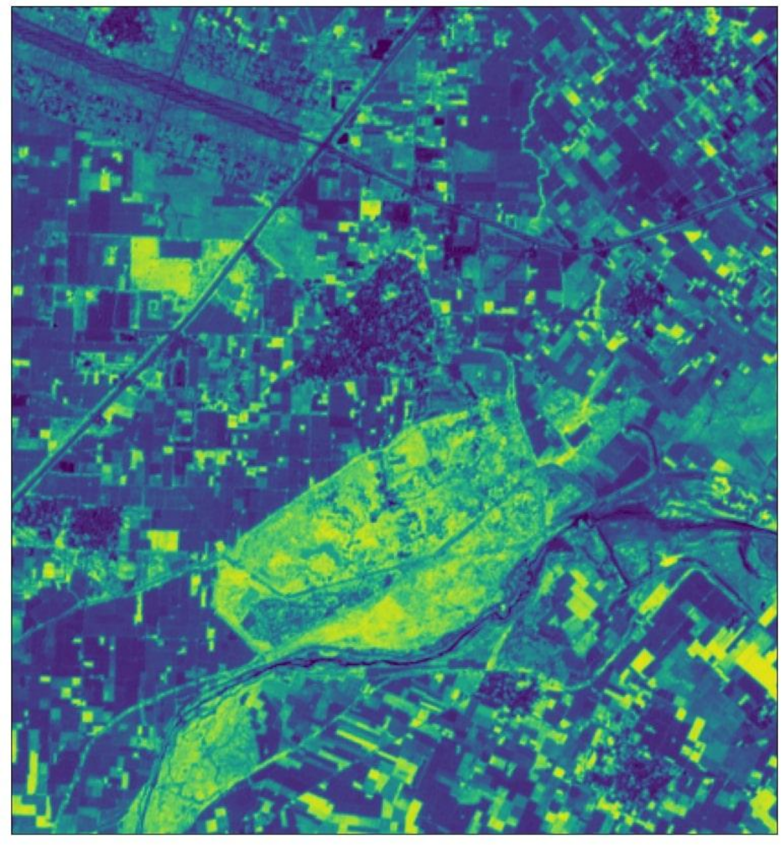



NDVI
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
classes
Forest
Urban
Farm
2020
2021
Year


Count
800
700
600
500
400
300
200
100
0
Forest
Urban
Farm
Classes

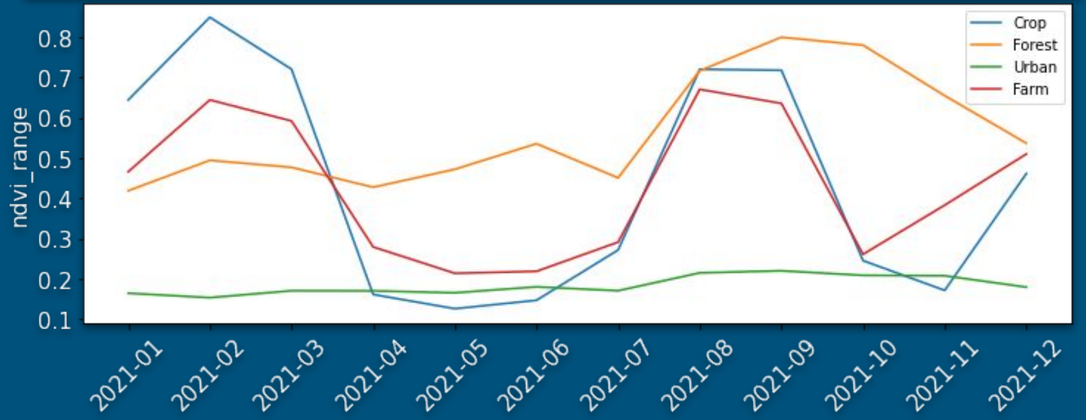

classes
Forest
Urban
Farm
Count
ndvi
gndvi
evi
evi2
ndwi
savi

4. NDVI (Normalized Difference Vegetation Index)

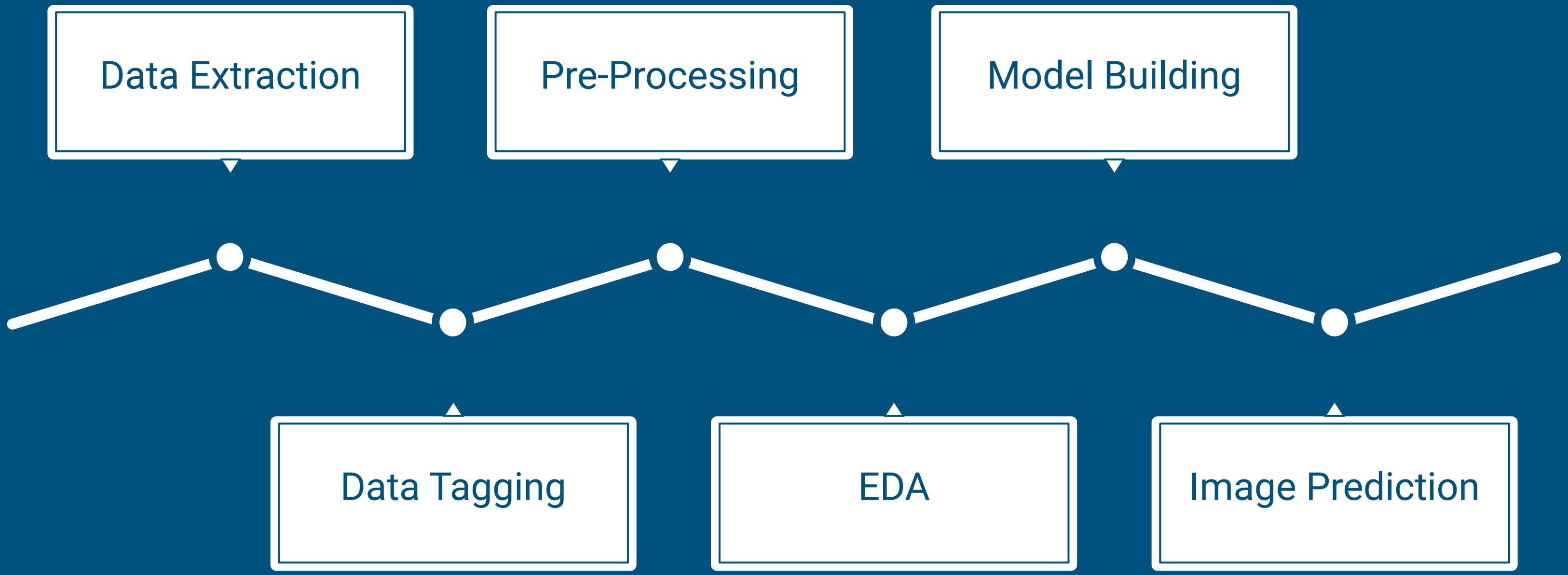


	2020-01	2020-02	2020-03	2020-04	2020-05	2020-06	2020-07	2020-08	2020-09	2020-10	2020-11	2020-12	classes
0	0.861357	0.873721	0.881716	0.687307	0.397143	0.198174	0.328520	0.499099	0.751683	0.453094	0.215066	0.497236	Crop
1	0.862032	0.877006	0.864203	0.667249	0.406250	0.179406	0.374352	0.501055	0.745652	0.474168	0.206150	0.499499	Crop
2	0.845688	0.864516	0.890530	0.660254	0.392857	0.183090	0.365090	0.525344	0.715474	0.480398	0.205415	0.512356	Crop
3	0.769880	0.802474	0.825983	0.412794	0.286482	0.193710	0.510644	0.585070	0.652702	0.368717	0.220370	0.524652	Crop
4	0.828367	0.814870	0.806950	0.202729	0.139588	0.164014	0.647543	0.629525	0.615667	0.245471	0.164381	0.594667	Crop
...	...	...	...	...	...	...	...	...	...	...	...	...	...
2695	0.730114	0.324915	0.213629	0.361018	0.333709	0.454340	0.471291	0.622390	0.702256	0.628040	0.508322	0.183647	Farm
2696	0.808784	0.222720	0.231382	0.395661	0.396825	0.145132	0.504580	0.211047	0.677266	0.172073	0.599009	0.740906	Farm
2697	0.765160	0.190523	0.238769	0.440719	0.487336	0.125352	0.578150	0.563549	0.602038	0.146873	0.437524	0.712402	Farm
2698	0.833637	0.882299	0.842652	0.223408	0.133976	0.109050	0.189434	0.456706	0.712135	0.427437	0.203530	0.683057	Farm
2699	0.873085	0.858693	0.790684	0.185355	0.152995	0.131629	0.120041	0.447992	0.683398	0.504167	0.221444	0.616448	Farm

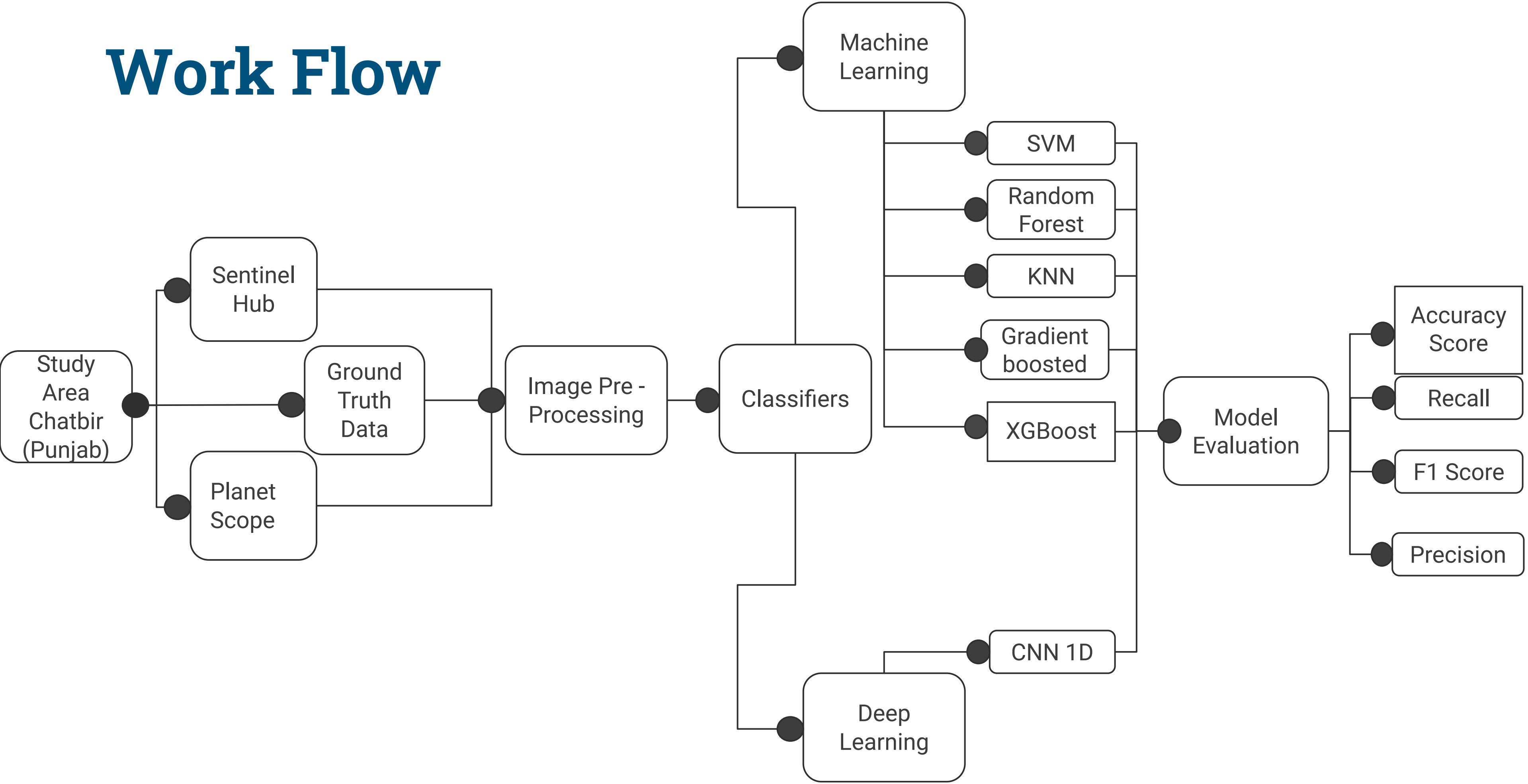
2700 rows × 13 columns



Methodology

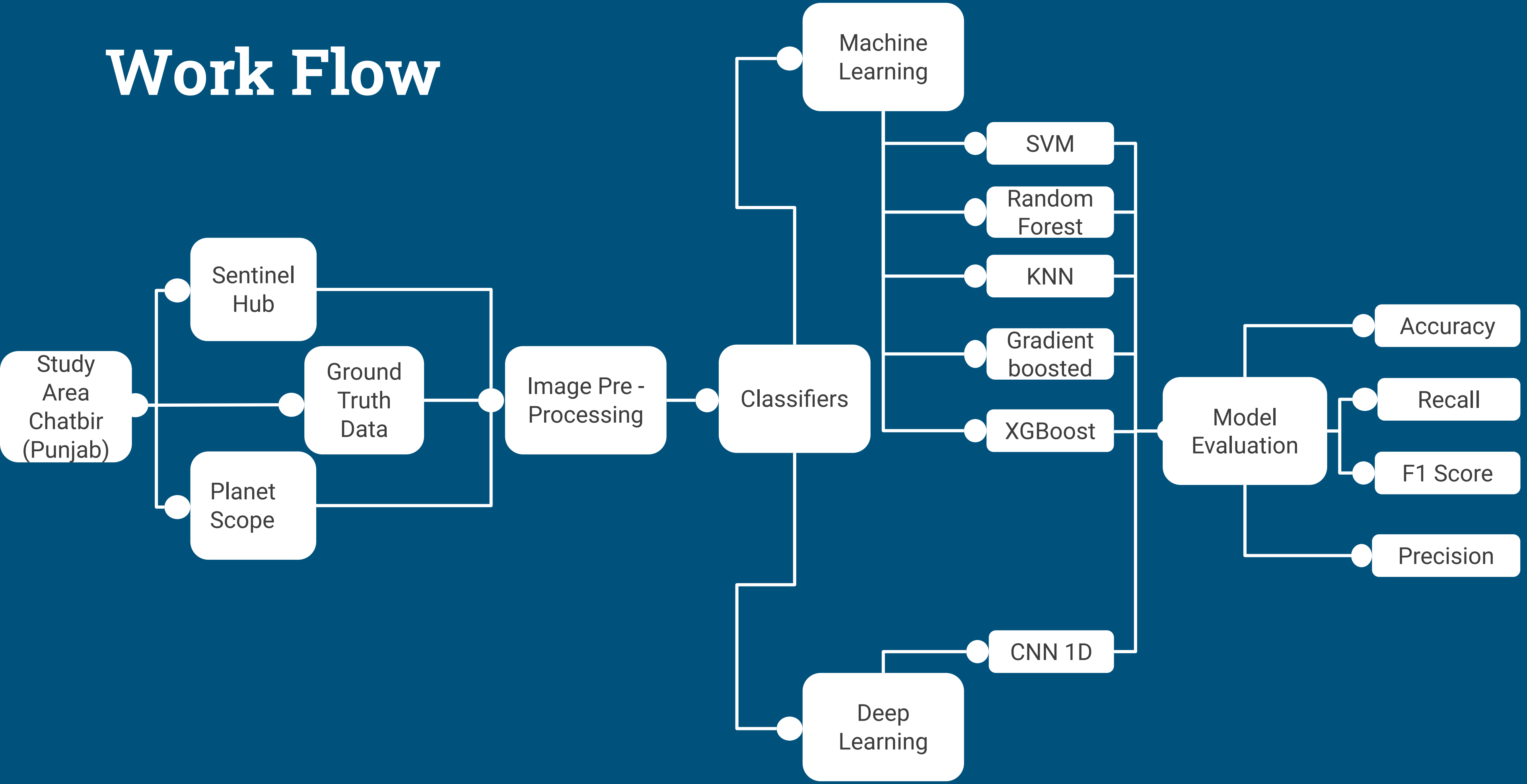


Work Flow



Study Area Chatbir (Punjab)
Sentinel Hub
Ground Truth Data
Planet Scope
Image Pre - Processing
Classifiers
Machine Learning
SVM
Random Forest
KNN
Gradient boosted
XGBoost
Deep Learning
CNN 1D
Model Evaluation
Accuracy Score
Recall
F1 Score
Precision

Work Flow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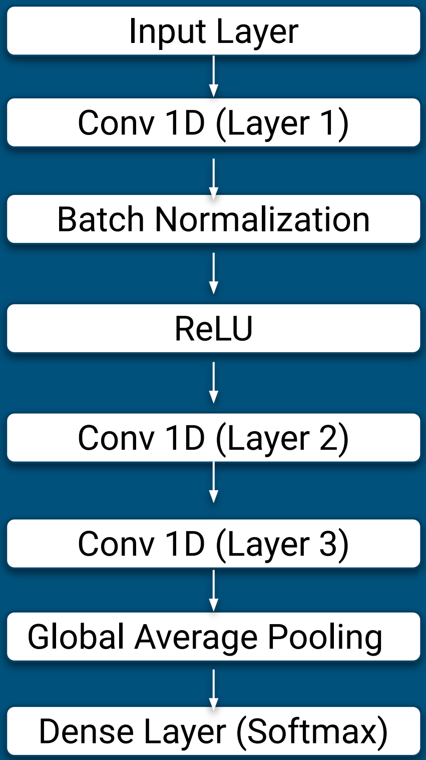
Accuracy
Recall
F1 Score
Precision

Model Design (CNN 1D)




```
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, 12, 1)]           0

 conv1d (Conv1D)             (None, 12, 64)            256

 batch_normalization (BatchN  (None, 12, 64)           256
 ormalization)

 re_lu (ReLU)                (None, 12, 64)            0

 conv1d_1 (Conv1D)           (None, 12, 64)            12352

 batch_normalization_1 (Batc  (None, 12, 64)           256
 hNormalization)

 re_lu_1 (ReLU)              (None, 12, 64)            0

 conv1d_2 (Conv1D)           (None, 12, 64)            12352

 batch_normalization_2 (Batc  (None, 12, 64)           256
 hNormalization)

 re_lu_2 (ReLU)              (None, 12, 64)            0

 global_average_pooling1d (G  (None, 64)               0
 lobalAveragePooling1D)

 dense (Dense)               (None, 3)                 195

=================================================================
Total params: 25,923
Trainable params: 25,539
Non-trainable params: 384
_________________________________________________________________
```

Results

Machine Learning (Farm, Forest and Urban)

	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	

*number of features -> 12 Months (January - December)

Machine Learning (Wheat, Forest and Urban)

	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	

*number of features -> 6 Months (October - April)

Machine Learning (Rice, Forest and Urban)

	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
SVM	Forest	0.99	0.93	0.96	0.92	0.82	0.87	0.83	0.87	0.76	0.83
	Rice	0.95	0.86	0.90		0.86		0.86		0.81	
	Urban	0.87	0.97	0.91		0.91		0.92		0.90	
XGBoost	Forest	0.99	0.90	0.94	0.93	0.11	0.69	0.57	0.71	0.69	0.76
	Rice	0.97	0.91	0.94		0.69		0.70		0.76	
	Urban	0.88	0.97	0.93		0.89		0.78		0.80	
Random Forest	Forest	0.99	0.94	0.96	0.97	0.41	0.76	0.19	0.75	0.63	0.72
	Rice	0.97	0.99	0.98		0.74		0.72		0.69	
	Urban	0.95	0.97	0.96		0.93		0.87		0.81	
Gradient Boosted	Forest	0.99	0.90	0.95	0.96	0.22	0.73	0.48	0.78	0.77	0.70
	Rice	0.98	0.99	0.99		0.71		0.75		0.64	
	Urban	0.93	0.98	0.96		0.95		0.98		0.69	
KNN	Forest	0.99	0.93	0.96	0.92	0.59	0.80	0.78	0.87	0.73	0.84
	Rice	0.98	0.82	0.89		0.77		0.84		0.81	
	Urban	0.85	0.98	0.91		0.94		0.95		0.94	

*number of features -> 5 Months (June - October)

Deep Learning (CNN 1D)

		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**		

*number of features -> 12 Months (January - December)

Deep Learning (CNN 1D)

Sentinel Hub (2021) Train (70) and Test (30) Split

testing accuracy: 0.9607535321821036

Predicted / Actual	Farm	Forest	Urban
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

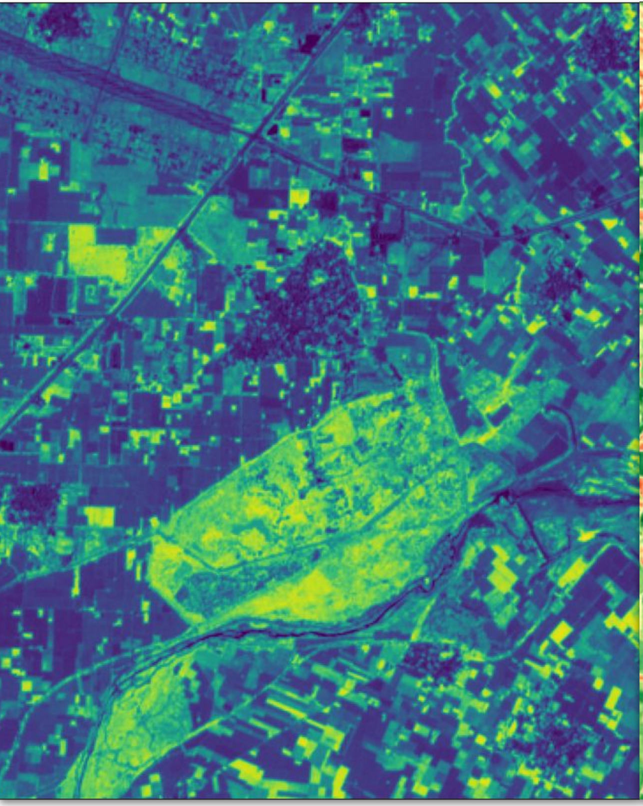
Planet Scope (2021) Train (70) and Test (30) Split

testing accuracy: 0.9737654320987654

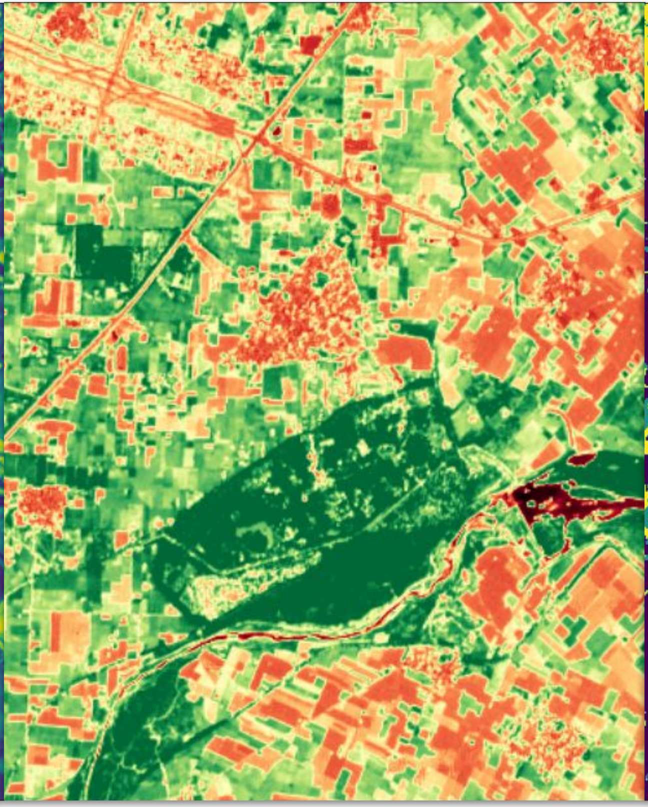
Predicted / Actual	Farm	Forest	Urban
Farm	209	4	2
Forest	1	183	2
Urban	8	0	239

	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

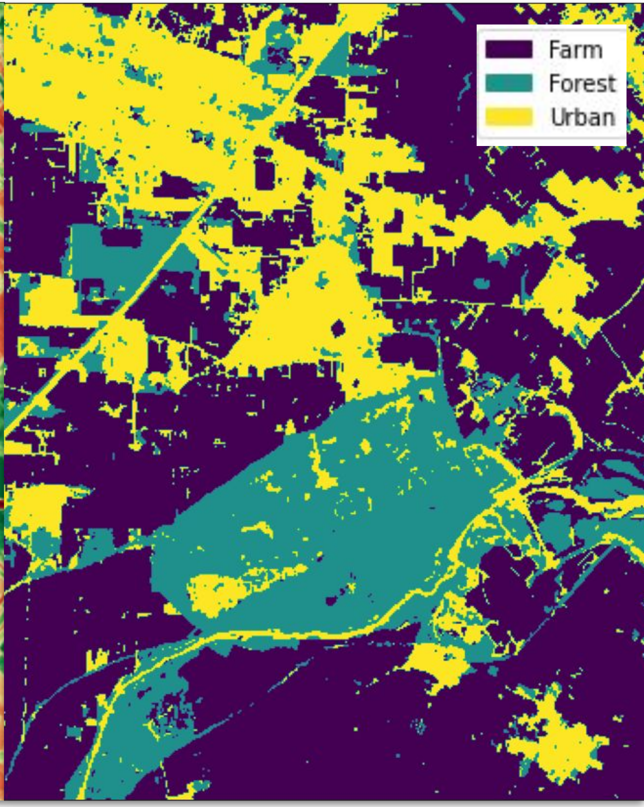
*number of features -> 12 Months (January - December)



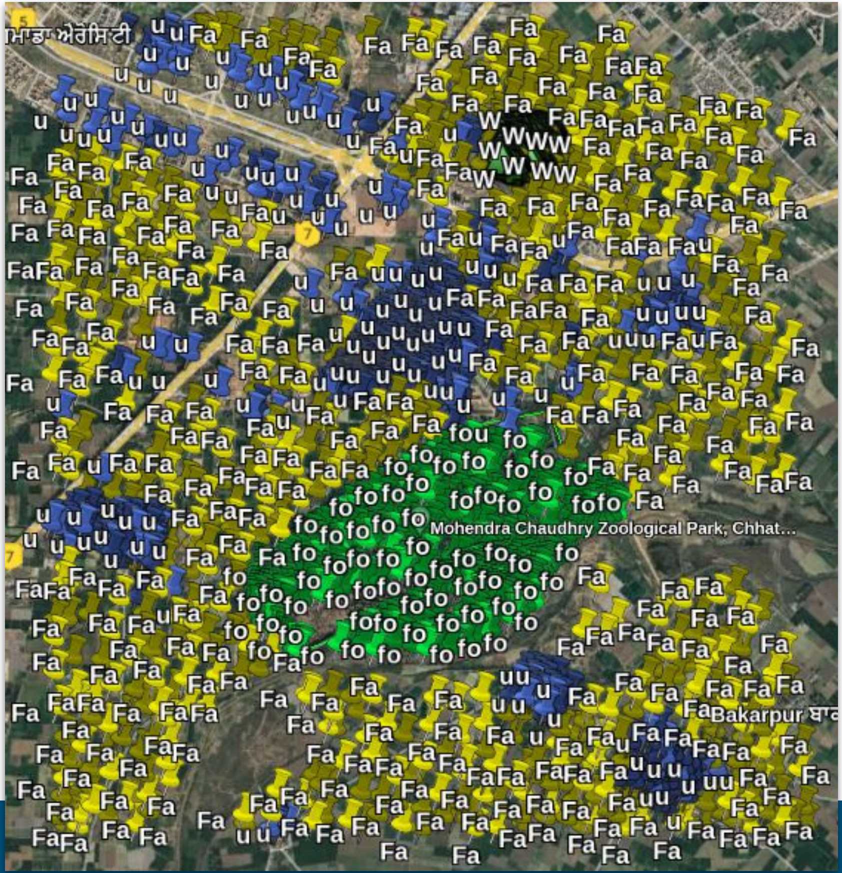
NDVI

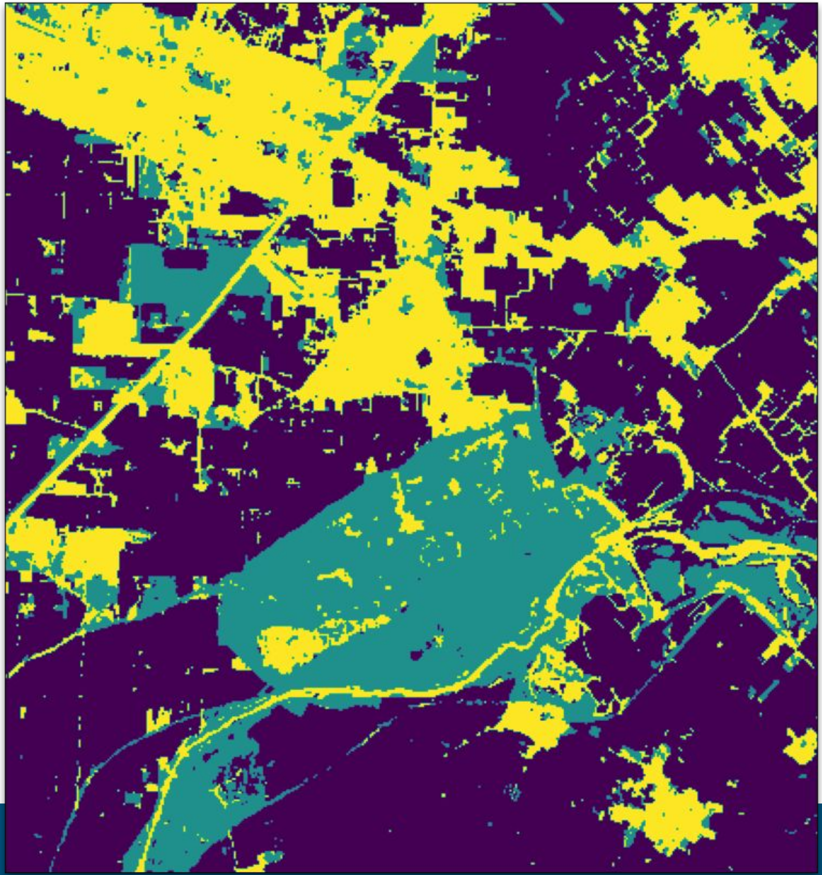


Color Coded



Predicted





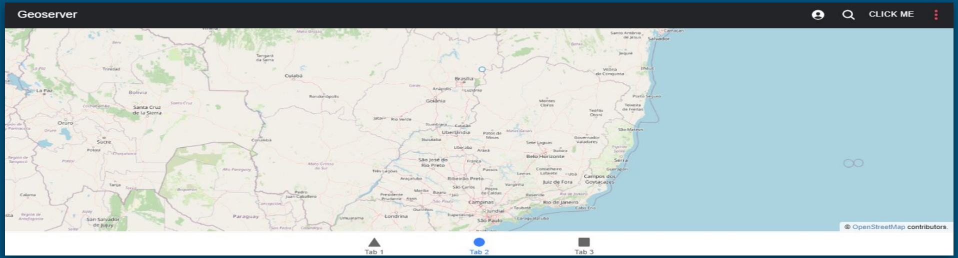
Tagged

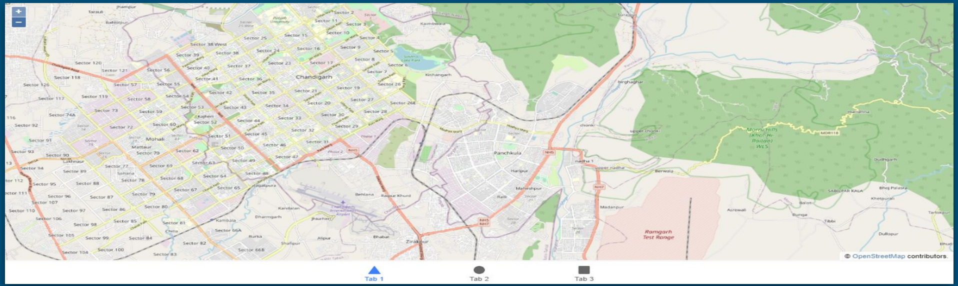
Predicted

Area -> 453px X 419px = 1,89,807 pixels

Geospatial Application

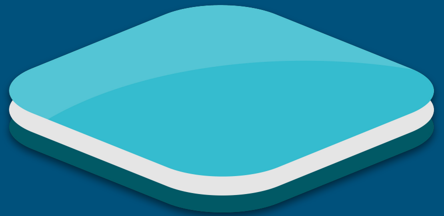
- Ionic Vue projects ship with the same tooling as regular Vue CLI projects.
- Ionic has three main options to start the app: tabs, side menu and blank. In this example we will use the "tabs" option. The "myVueApp" is our app name.
- It enables us to build fully functional and advanced mobile apps using web technologies.
- An application created using Ionic Framework is a cross-platform app.
- It is built like a simple web app, but allows us to generate a native app. It has access to all functionalities specific to the phone.

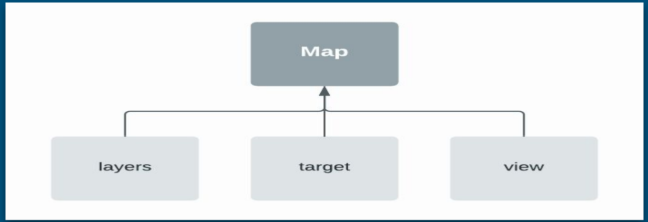




Openlayers Map and Web Map

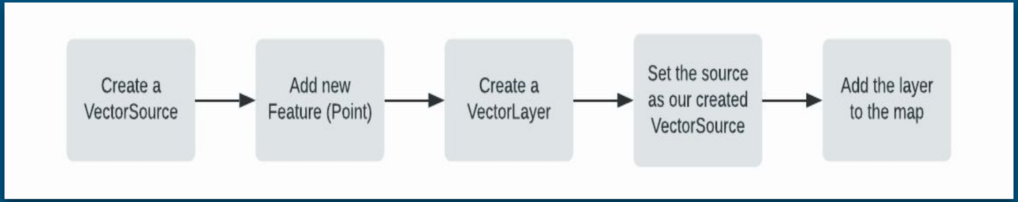
- OpenLayers makes it easy to put a dynamic map in any web page. It can display map tiles, vector data and markers loaded from any source.
- OpenLayers has been developed to further the use of geographic information of all kinds. It is completely free, Open Source JavaScript, released under the 2-clause BSD License (also known as the FreeBSD).





Features

- Tiled Layers
- Vector Layers
- Cutting Edge, Fast & Mobile Ready
- Easy to Customize and Extend

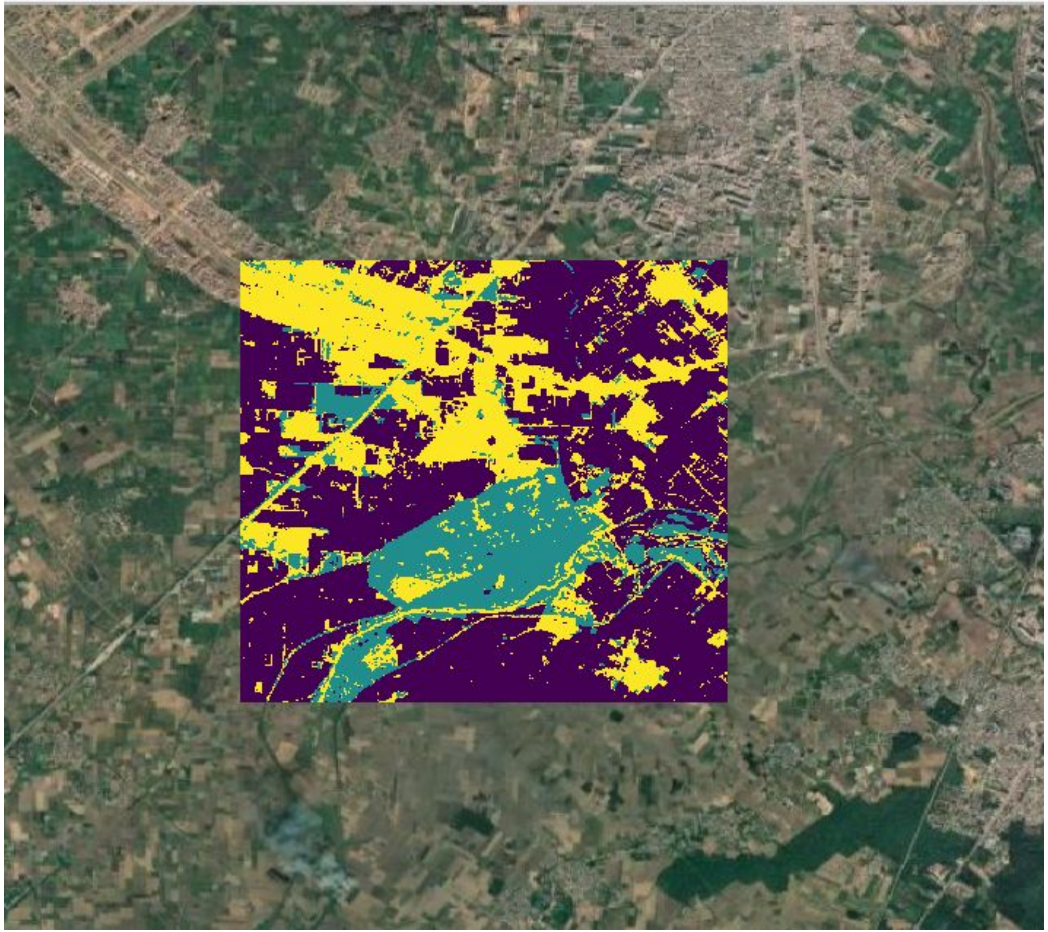


Geoserver

Introduction

- GeoServer implements industry standard OGC protocols such as Web Feature Service (WFS), Web Map Service (WMS), and Web Coverage Service (WCS).
- Additional formats and publication options are available as extensions including Web Processing Service (WPS), and Web Map Tile Service (WMTS).
- It is designed for interoperability and excels at publishing any major spatial data source using open standards. With suitable preparation of data it excels at handling very large datasets, both raster and vector.

Rendered Image



Conclusion and Future work

Conclusion

- Started with extracting data from open source (Sentinel Hub)
- Color coded to detect cloud images and removal of clouds data
- Created ground truth tagged dataframe from google earth explorer
- Applied Machine learning or deep learning algos and tested over multiple years
- Visualization of predicted vs original image
- We found that CNN 1D algorithm among all is giving the best accuracy for all the years.
- Comparison between two different datasets (Sentinel Hub and Planet Scope)

Future Work

- Testing and Generalizing the best model for larger area.
- Different Crop Classification
- Finalize the package for Sentinel Hub API and make it public so that researchers can extract the data for their interested area of research.
- PostgreSql can be used to store the spatial data of the different crops for different years.

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Thank You

“Wallowing on the smooth surface of their self-satisfaction, many are merely counting the shadows on the wall of their ennui, adding up the numerous illusions and indulging in the comforting lies and ignoring the unpleasant truths. (“Bread and Satellite”)”

Questions?