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Elevating Forestry Prediction: A Study on Machine Learning Model for Plantations Survival Rate Analysis

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Abstract: This paper details the development and preliminary findings of a machine learning model designed to predict the survival rate of plantations. Drawing data from official sources, various vegetation indices were used as features for the predictive model. Initial results show potential, despite certain limitations, suggesting avenues for further enhancement and application.

I. INTRODUCTION

Plantations play a significant role in environmental conservation and economic sustenance. Predicting their survival rates becomes essential for sustainable development and forest management. With advancements in remote sensing and machine learning, this research aims to develop a predictive model using satellite imagery indices and the Gradient Boosted Trees algorithm to determine the survival rate of plantations.

II. STUDY AREA

The study area includes plantations done by MP Forest Department in East Chhindwara Division from 2015 to 2018.

III. METHODOLOGY

A. Data Collection

The primary source for the research data was the Madhya Pradesh Forest Department's official portal www.mpforest.gov.in, from which the Plantation Survival Report and KMLs of plantations were extracted.

Plt ID	Circle	Division	Range	Beat	Compt	Category	Plt.Year	Scheme	2015 Pre	2015 Post	2016 Pre	2016 Post	2017 Pre	2017 Post	2018 Pre	2018 Post	2019 Pre	2019 Post	2020 Pre	2020 Post	2021 Pre
19282	Chhindwara	East Chhindwara	Amarwara	Devangao	1208 RF	Teak	2015	Working Plan Implementation		90	86.06	82.03	80.92	76.47	60	58	56.92	59.23	58.85		
19283	Chhindwara	East Chhindwara	Amarwara	Ghatsaliwara	1191 RF	Misc	2015	Working Plan Implementation		82	74.53	71.45	68.76	67.15	65.02	64.28	57.17	64.27	61.03		
19393	Chhindwara	East Chhindwara	Amarwara	Putra	1183 RF	Bamboo	2015	Working Plan Implementation		85	80.46	78.39	76.21	75.44	78	75	70.4	65	65		
20356	Chhindwara	East Chhindwara	Amarwara	Bagla	1216 RF	Teak	2016	Others				92.47	91.04	87.62	79	93.71	90	72.86	69.86	65.43	60
20357	Chhindwara	East Chhindwara	Amarwara	Surlakhapa	1158 PF	Teak	2016	Others				91.51	87.46	83.87	77.57	82	70.29	62.93	62.18	48.39	45.36
20358	Chhindwara	East Chhindwara	Amarwara	Sarsdol	1230 RF	Teak	2016	Others				94.9	88.17	81.99	85	85	82	79.54	79.4	77.1	59.42
20359	Chhindwara	East Chhindwara	Amarwara	Karapatha	1142 PF	Teak	2016	Others				88.57	82.22	78.6	75.14	84	74	70	69.14	67.71	63.86
20362	Chhindwara	East Chhindwara	Amarwara	Amarwara	1226 PF	Teak	2016	Others				91.26	81.55	74.87	80	80	68	68	65.4	60.4	55.7
20363	Chhindwara	East Chhindwara	Amarwara	Dungariya	1189 RF	Teak	2016	Others				82.64	75.6	66.42	80	88	82.25	79	78.09	71.71	70.13
20364	Chhindwara	East Chhindwara	Amarwara	Medki	1131 PF	Bamboo	2016	Others				92.64	89.98	86.78	85	90	74	70.08	64	58	54
20365	Chhindwara	East Chhindwara	Amarwara			Misc	2016	Environment Forestry				95.81	91.95	74.77	85	80	75	75	72.33	66.84	60.7
20374	Chhindwara	East Chhindwara	Amarwara	Medki	1131 PF	Bamboo	2016	Others				93.18	86.53	80.51	75	90	71	85.12	80	63	60
20375	Chhindwara	East Chhindwara	Amarwara	Gourpani	1126 PF	Bamboo	2016	Others				91.21	84.85	78.45	87	95	71	69.12	62.98	53	50
52124	Chhindwara	East Chhindwara	Amarwara	Bhajipani	1175 RF	Bamboo	2017	Others						94.5	80	95	92.92	90	85	81	71
52134	Chhindwara	East Chhindwara	Amarwara	Dulara	1166 RF	Misc	2017	Others						95.6	80	90	88	89.52	85	83	75
52135	Chhindwara	East Chhindwara	Amarwara	Dhasanwara	1178 RF	Misc	2017	Compensatory Afforestation						93.5	78	95	91.01	95.01	93.26	90.25	89.73
52136	Chhindwara	East Chhindwara	Amarwara	Devangao	1208 RF	Misc	2017	Compensatory Afforestation						95	76.16	95	90.24	94.33	94.24	94.46	94.15
52153	Chhindwara	East Chhindwara	Amarwara	Sarsdol	1230 RF	Misc	2017	Others						95.02	75.02	75.02	72	72.25	72	70.46	59.08
52154	Chhindwara	East Chhindwara	Amarwara	Kubri	1252 RF	Misc	2017	Others						89	90	95	80	78	77	76	70
52155	Chhindwara	East Chhindwara	Amarwara	Gadadaryaw	1159 RF	Misc	2017	Others						90.13	70.13	90.13	88	84	73.87	68	66.67
52156	Chhindwara	East Chhindwara	Amarwara	Putra	1180 RF	Misc	2017	Others						92	80	90	87.75	88	88	88	88
52811	Chhindwara	East Chhindwara	Amarwara	Karapatha	1142 PF	Misc	2017	Compensatory Afforestation						98.8	78	90	84	89	87.61	83.94	82.7
94510	Chhindwara	East Chhindwara	Amarwara	Sariyapani	1248 RF	Misc	2018	Working Plan Implementation								95	93	93.33	90	80	70
94511	Chhindwara	East Chhindwara	Amarwara	Sariyapani	1248 RF	Misc	2018	FDA (NAP)								95	90	94.02	78.05	65	55
94512	Chhindwara	East Chhindwara	Amarwara	Devangao	1208 RF	Misc	2018	FDA (NAP)								95	91.7	93.12	90.7	87	73.95
105362	Chhindwara	East Chhindwara	Amarwara	Chimouaa	1223 RF	Misc	2019	Compensatory Afforestation										100	90.18	86.4	86.24
105363	Chhindwara	East Chhindwara	Amarwara	Karapatha	1142 PF	Misc	2019	Compensatory Afforestation										96	88	89.98	77.76
105364	Chhindwara	East Chhindwara	Amarwara	Chimouaa	1224 RF	Misc	2019	Compensatory Afforestation										100	90.02	86.4	86.08
105365	Chhindwara	East Chhindwara	Amarwara	Chimouaa	1224 RF	Misc	2019	Compensatory Afforestation										100	95.2	83.2	79.2
105366	Chhindwara	East Chhindwara	Amarwara	Tendani	1222 RF	Misc	2019	Compensatory Afforestation										100	80	77.6	83.2
105367	Chhindwara	East Chhindwara	Amarwara	Bagla	1216 RF	Misc	2019	Compensatory Afforestation										100	80	80	80
105368	Chhindwara	East Chhindwara	Amarwara	Thavari	1173 PF	Misc	2019	Compensatory Afforestation										98	95.2	92.4	81.6
105369	Chhindwara	East Chhindwara	Amarwara	Devangao	1208 RF	Misc	2019	Compensatory Afforestation										99.53	99	98.64	97.84
105370	Chhindwara	East Chhindwara	Amarwara	Sejwara	1144 PF	Misc	2019	Working Plan Implementation										98.75	92.5	97	92.65
105770	Chhindwara	East Chhindwara	Amarwara	Medki	1132 PF	Misc	2019	Working Plan Implementation										97.54	94	86	83
105771	Chhindwara	East Chhindwara	Amarwara	Baratmari	1137 PF	Misc	2019	Working Plan Implementation										96.48	80	85	80
105772	Chhindwara	East Chhindwara	Amarwara	Tinsai	1147 PF	Misc	2019	Working Plan Implementation										99	94	89.38	86

Fig.1 Survival Report of Plantations

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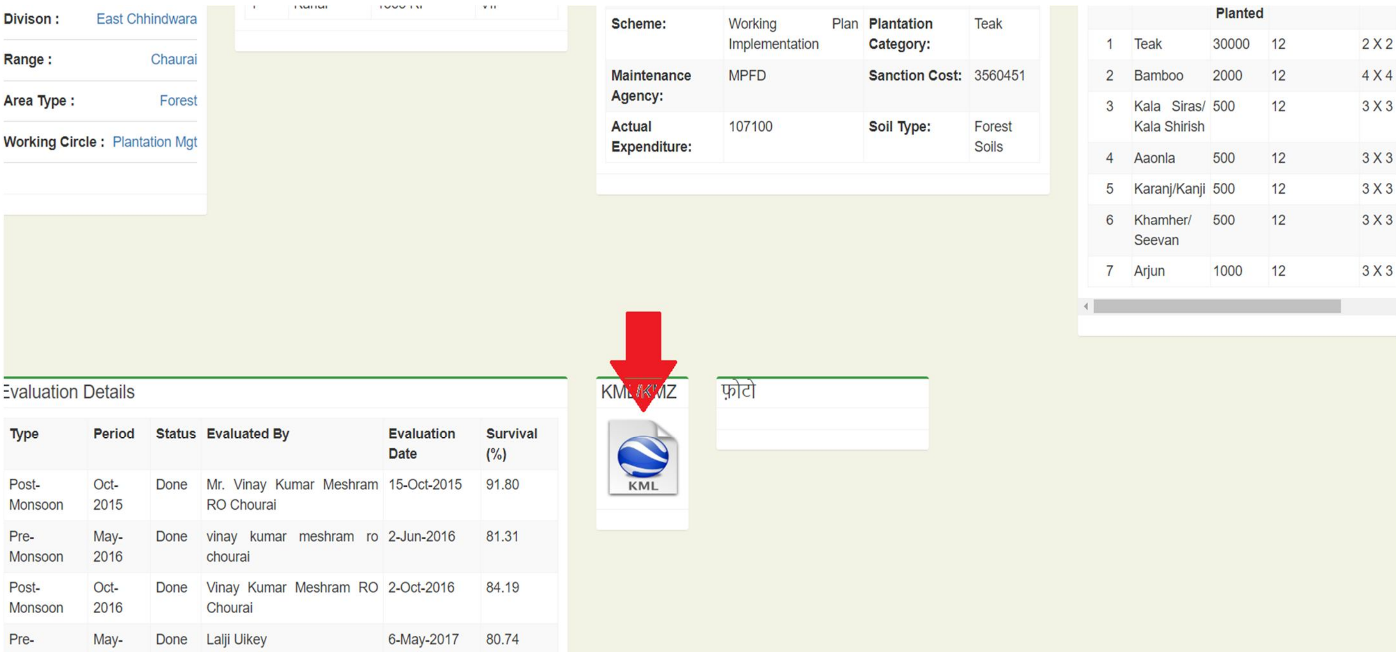

Fig.2 KML file of Plantations download

B. *Data Processing*

The KMLs are then checked for their geometrical validity and then KMLs of plantations of same year are merged to have shapefile containing geometries of all plantations of same year .

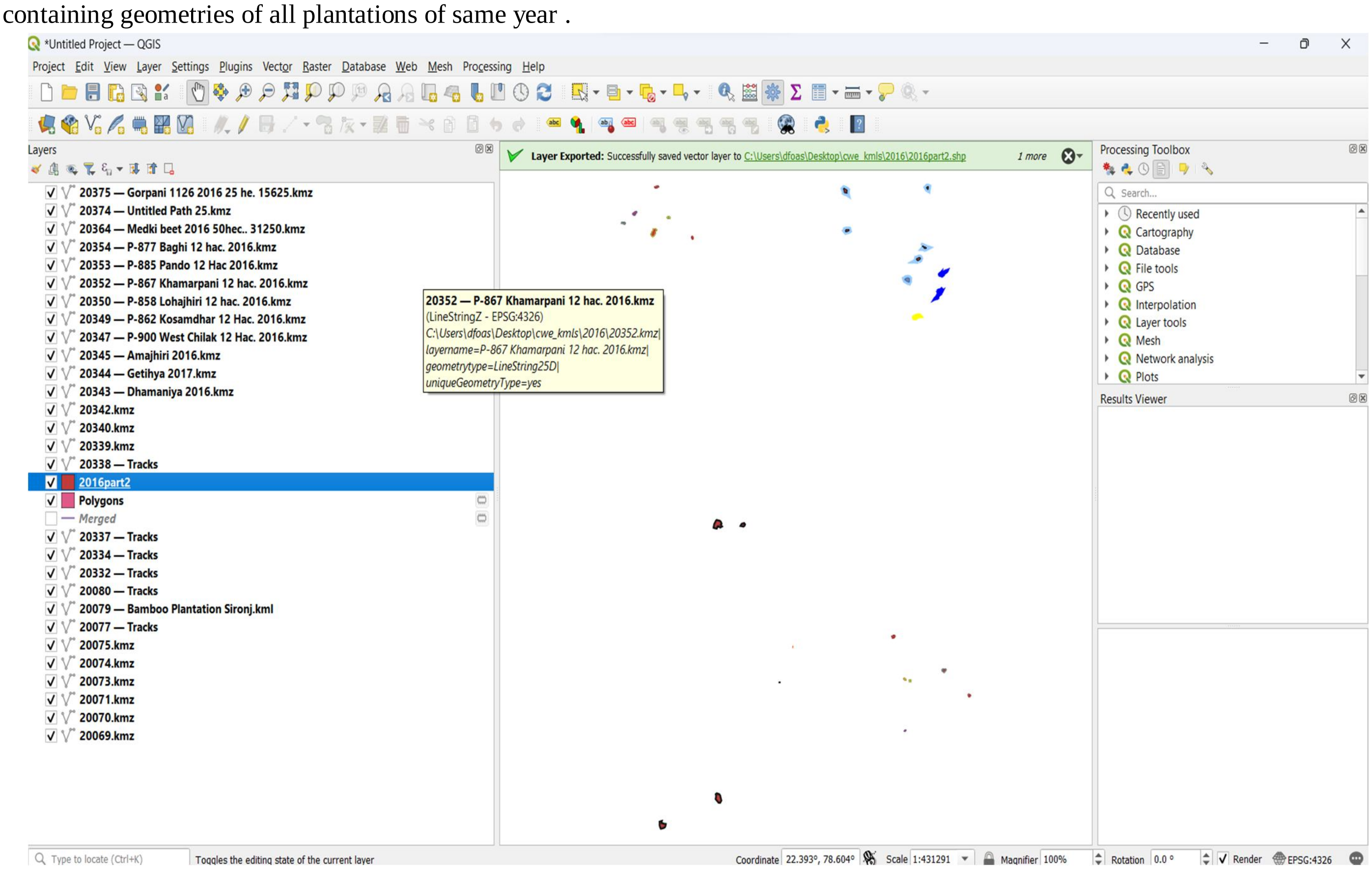

Fig.3 KML files Processing in QGIS

C. Calculations

Satellite imagery indices, including NDVI (Normalized Difference Vegetation Index), MCARI (Modified Chlorophyll Absorption Ratio Index), SAVI (Soil-Adjusted Vegetation Index), MSI (Moisture Stress Index), and NDWI (Normalized Difference Water Index), were considered. These indices provide crucial insights into vegetation health, soil moisture, chlorophyll content, and water stress, making them imperative for analyzing plantation survival.

Using Google Earth Engine, the slope of these indices was determined over a five-year span to track and understand growth trends. The code takes input as shapefile containing geometries of all plantations of particular year and output as CSV file containing slope trends of all indices and plantation ID.

```
// Improved cloud and shadow masking using the SCL band.
var maskCloudsAndShadows = function(image) {
  var SCL = image.select('SCL');
  var mask = SCL.neq(3).and(SCL.neq(8)).and(SCL.neq(9)).and(SCL.neq(10)).and(SCL.neq(2));
  return image.updateMask(mask);
};

// Function to convert system:time_start metadata to a band.
var addTimeBand = function(image) {
  // Convert milliseconds from Unix epoch to years since 2000 for improved numerical stability
  var yearsSince2000 = image.metadata('system:time_start').divide(1000 * 60 * 60 * 24 * 365.25).subtract(2000);
  return image.addBands(yearsSince2000.rename('time'));
};

// Load Sentinel-2 Surface Reflectance data.
var collection = ee.ImageCollection('COPERNICUS/S2_SR')
    .filterDate('2016-01-01', '2022-01-01')
    .filterBounds(regions) // Adjust as per your requirements
    .map(maskCloudsAndShadows);

// Compute NDVI, SAVI, NDWI, MCARI, MSI for each image in the collection.
var computeIndices = function(image) {
  var ndvi = image.normalizedDifference(['B8', 'B4']).rename('NDVI');
  var savi = image.expression(
    '((B8 - B4) / (B8 + B4 + 0.5)) * 1.5',
    { 'B8': image.select('B8'), 'B4': image.select('B4') }
  ).rename('SAVI');

  var ndwi = image.normalizedDifference(['B3', 'B8']).rename('NDWI');
  var mcari = image.expression(
    '0.2 * (2.5 * (NIR - RED) - 1.3 * (NIR - BLUE))',
    {
      'NIR': image.select('B8'),
      'RED': image.select('B4'),
```

```
    'BLUE': image.select('B2')
   }
  ).rename('MCARI');

  var msi = image.select('B11').divide(image.select('B8')).rename('MSI');

  return image.addBands([ndvi, savi, ndwi, mcari, msi]);
};

var withIndices = collection.map(computeIndices).map(addTimeBand);

// Compute the linear trend over time for each index.
var trendNDVI = withIndices.select(['time', 'NDVI']).reduce(ee.Reducer.linearFit());
var trendSAVI = withIndices.select(['time', 'SAVI']).reduce(ee.Reducer.linearFit());
var trendNDWI = withIndices.select(['time', 'NDWI']).reduce(ee.Reducer.linearFit());
var trendMCARI = withIndices.select(['time', 'MCARI']).reduce(ee.Reducer.linearFit());
var trendMSI = withIndices.select(['time', 'MSI']).reduce(ee.Reducer.linearFit());

// Compute the slope for each region for each index
var computeSlopesForRegion = function(feature) {
  var slopes = {
   'slope_NDVI': trendNDVI.reduceRegion({ reducer: ee.Reducer.mean(), geometry: feature.geometry(), scale: 10, maxPixels: 1e9
}).get('scale'),
   'slope_SAVI': trendSAVI.reduceRegion({ reducer: ee.Reducer.mean(), geometry: feature.geometry(), scale: 10, maxPixels: 1e9
}).get('scale'),
   'slope_NDWI': trendNDWI.reduceRegion({ reducer: ee.Reducer.mean(), geometry: feature.geometry(), scale: 10, maxPixels:
1e9 }).get('scale'),
   'slope_MCARI': trendMCARI.reduceRegion({ reducer: ee.Reducer.mean(), geometry: feature.geometry(), scale: 10, maxPixels:
1e9 }).get('scale'),
   'slope_MSI': trendMSI.reduceRegion({ reducer: ee.Reducer.mean(), geometry: feature.geometry(), scale: 10, maxPixels: 1e9
}).get('scale')
  };
  return feature.set(slopes);
};

var results = regions.map(computeSlopesForRegion);

// Export the results to a CSV
Export.table.toDrive({
  collection: results.select(['layer', 'slope_NDVI', 'slope_SAVI', 'slope_NDWI', 'slope_MCARI', 'slope_MSI']),
  description: 'index_trend_slopes',
  folder: 'YOUR_GOOGLE_DRIVE_FOLDER_NAME',
  fileNamePrefix: 'index_slopes',
  fileFormat: 'CSV'
});
```

Fig.4 Code Snippet Used

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index_slopes.csv

	A	B	C	D	E	F	G	H
1	system:index	Name	slope_MCARI	slope_MSI	slope_NDVI	slope_NDWI	slope_SAVI	.geo
2	0	19282	154.5343461	-0.2164081668	0.1377919358	-0.07101912856	0.2066520858	{"type":"Polygon","cc
3	1	19393	156.9190414	-0.2331009133	0.1429581158	-0.08724809969	0.2144030191	{"type":"Polygon","cc
4	2	19395	121.9599274	-0.08549358721	0.09398345108	-0.04240114477	0.1409526939	{"type":"Polygon","cc
5	4	19268	118.025751	-0.09823957037	0.0960210239	-0.05663429632	0.1440093	{"type":"MultiPolygor
6	5	19269	155.0995777	-0.1784348111	0.1150790121	-0.07415531469	0.1725999481	{"type":"Polygon","cc
7	6	19272	118.4652155	-0.2057260546	0.1049743431	-0.07113253121	0.1574418222	{"type":"MultiPolygor
8	7	19283	127.4521552	-0.1920846053	0.09566752602	-0.0601483986	0.1434838067	{"type":"MultiPolygor
9	8	19318	155.3514357	0.002409663849	0.1435519647	-0.08526188324	0.2152928245	{"type":"Polygon","cc
10	9	19390	177.7067534	-0.1923126285	0.1486470523	-0.08115190413	0.2229379396	{"type":"Polygon","cc
11	0000000000000000	19391	113.1864937	-0.1587692604	0.09479481155	-0.04193772272	0.1421676767	{"type":"Polygon","cc
12	0000000000000000	19392	61.75641322	-0.05044091273	0.04086791998	-0.01983820533	0.06129367215	{"type":"Polygon","cc
13	0000000000000000	19398	87.96906089	-0.1347571117	0.07816838872	-0.040547038	0.1172323646	{"type":"Polygon","cc
14	0000000000000000	19400	124.7826303	-0.1357711431	0.1119769377	-0.05095998663	0.1679373111	{"type":"Polygon","cc
15	0000000000000000	19401	151.0403436	-0.1629308578	0.1140908065	-0.05349684247	0.1711134672	{"type":"Polygon","cc
16	0000000000000000	19444	131.9218121	-0.130157687	0.1021965295	-0.05026357723	0.1532714987	{"type":"Polygon","cc
17	10	20045	122.7043572	-0.1588435103	0.1102083205	-0.06802105224	0.1652883545	{"type":"Polygon","cc
18	3	19399	139.2572438	-0.1347879132	0.1106562813	-0.05257724714	0.1659584235	{"type":"Polygon","cc

Fig.5 Output CSV file

D. Model Creation

Our dataset, housed within Google Sheets, encompassed 112 unique plantation records, each denoted by a Plantation ID. Each record detailed the slopes of satellite-derived indices, serving as predictive features for plantation survival rates. Using the "Simple ML for Sheets" extension, we streamlined machine learning directly within the spreadsheet, bypassing intricate coding processes.

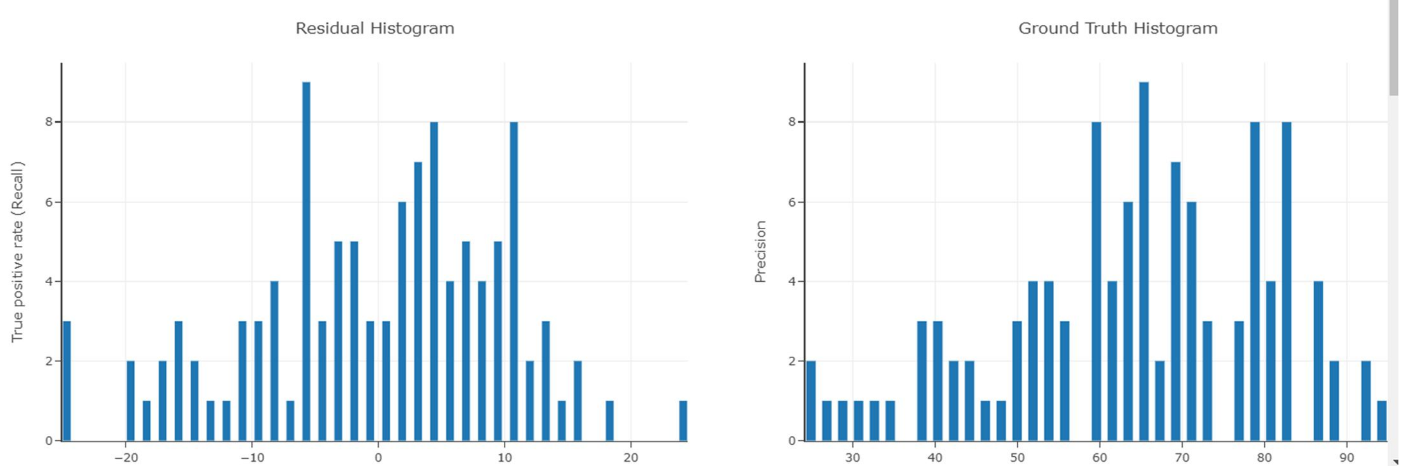
For the modelling:

1) *Data Labelling:* Plantation survival status after 5 years, extracted from official reports, was our target variable.
2) *Feature Selection:* Continuous slope values from indices like NDVI and SAVI became our independent variables, suitable for regression models.
3) *Model Training & Evaluation:* We employed the Gradient Boosted Trees algorithm for its robustness in handling vast datasets. The extension facilitated automatic data partitioning for training and validation, subsequently evaluating the model's accuracy on unseen data.

Model Evaluation

```
Number of predictions (without weights): 111
Number of predictions (with weights): 111
Task: REGRESSION
Label: SURVIVAL RATE

RMSE: 9.99285 CI95[X2][8.83349 11.5053]
Default RMSE: : 16.5915
```



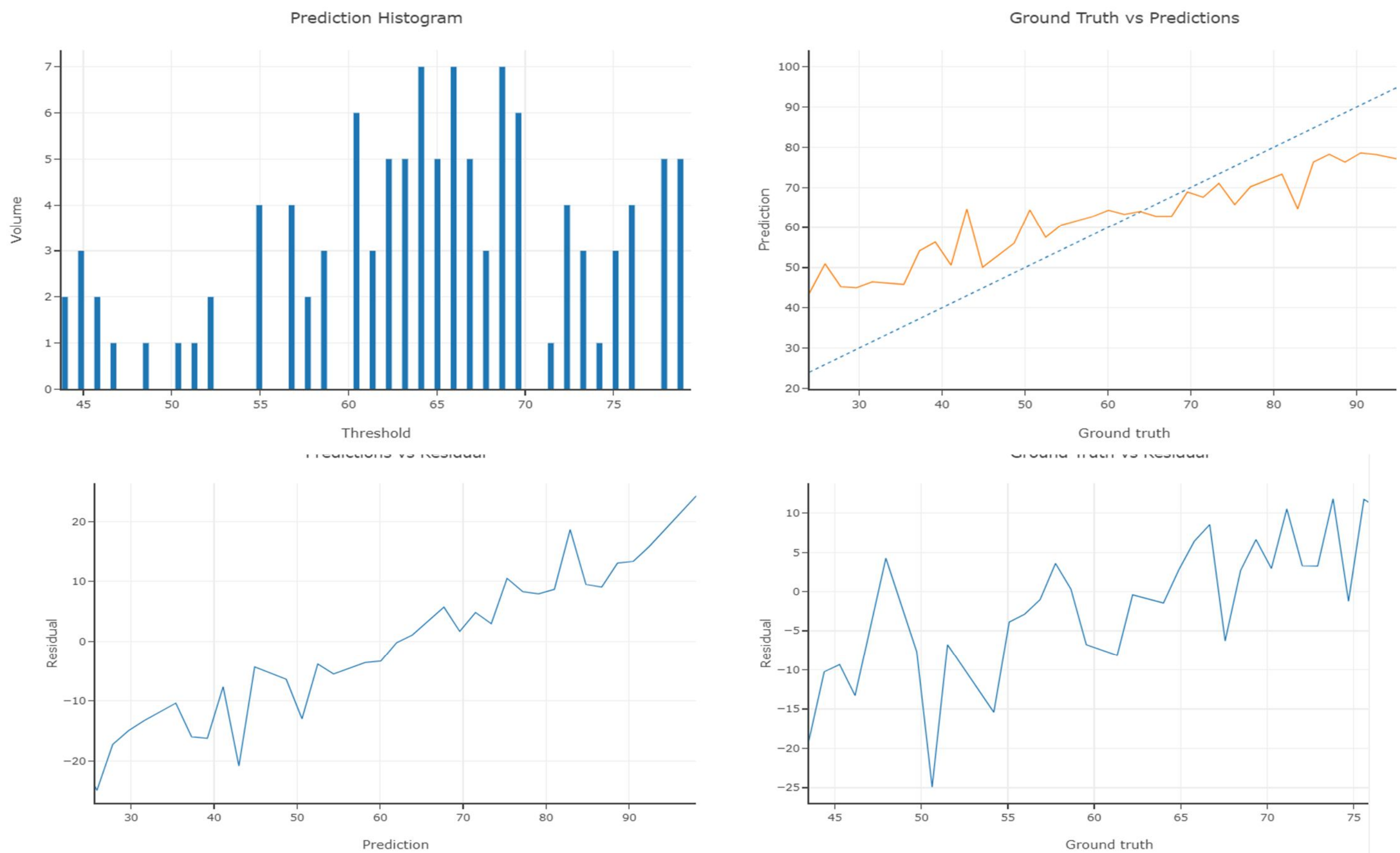


Fig.6 Model Evaluation Report

IV. RESULTS AND INTERPRETATION

Of the 112 plantations analysed, the model accurately predicted the survival of 91. The overall accuracy stood at 81.25%. However, the research encountered a limitation in the form of the database's restricted scope, sourced from just one forest division spanning four years only2015 to2018. Consequently, predictions for plantations with reduced survival rates showed significant errors.

V. DISCUSSION

The model, in its present iteration, holds potential, even if the accuracy isn't at an optimal level. Its primary value lies in assisting field officers in identifying plantations at risk. By flagging potential failures, proactive measures can be initiated to mitigate issues. For future iterations, it's imperative to diversify and expand the dataset. Incorporating additional indices and geometric features could further enhance the model's predictive capabilities.

VI. FUTURE WORK

1) Augmenting the dataset is a priority, ensuring diverse data sources to refine the model further.
2) New indices and geometric parameters, especially features like land surface temperature, will be considered in the updated model.
3) Plans to automate the entire model are underway using platforms such as Google Colab, making the process more user-friendly.

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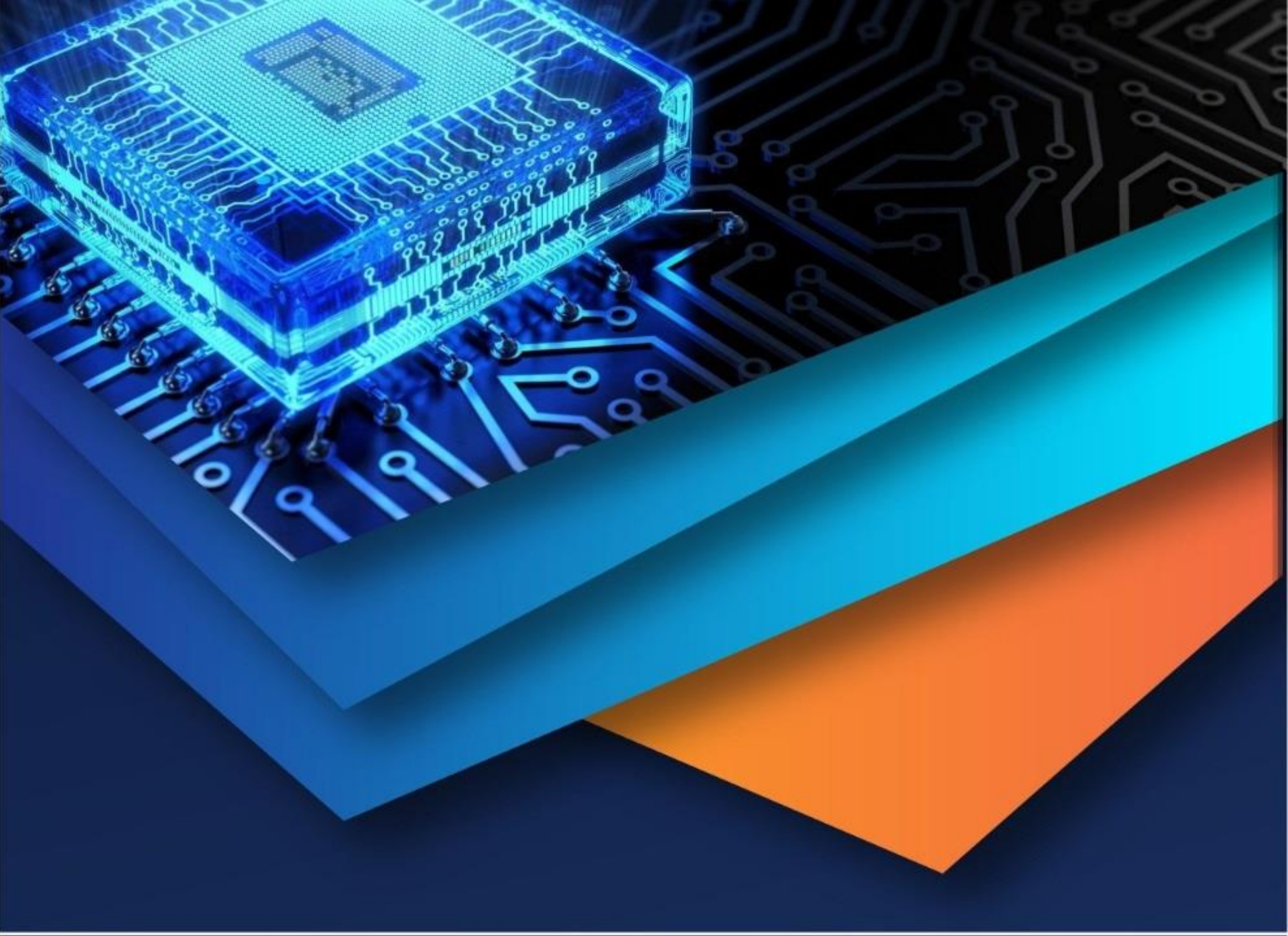
[3] Arain, A. (Year not specified). Machine Learning Approach to Quantify Leaf Depletion. github.com/Arain23



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