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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 PF	Teak	2016	Working Plan Implementation		90	86.06	82.03	80.92	76.47	80	58	58.92	53.23	58.85		
19283	Chhindwara	East Chhindwara	Amarwara	Ghatsaliwara	1191 PF	Misc	2016	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 PF	Bamboo	2016	Working Plan Implementation		85	80.46	78.38	76.21	75.44	78	75	70.4	65	65		
20296	Chhindwara	East Chhindwara	Amarwara	Bagla	1216 PF	Teak	2016	Others				92.47	91.04	87.62	79	83.71	90	72.88	89.86	65.43	60
20297	Chhindwara	East Chhindwara	Amarwara	Surlakhapa	1168 PF	Teak	2016	Others				94.9	87.46	83.87	77.57	82	70.28	62.93	62.18	48.39	45.38
20298	Chhindwara	East Chhindwara	Amarwara	Sarsdol	1230 PF	Teak	2016	Others				94.9	88.17	81.99	85	85	82	79.54	79.4	77.1	59.42
20299	Chhindwara	East Chhindwara	Amarwara	Karagatha	1142 PF	Teak	2016	Others				88.57	82.22	78.6	75.14	84	74	70	69.14	67.71	63.88
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	Dungajia	1189 PF	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	88.98	86.78	85	90	74	70.08	64	59	54
20365	Chhindwara	East Chhindwara	Amarwara	Medki	1131 PF	Misc	2016	Environment Forestry				95.81	91.98	74.77	88	80	75	78	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	65.12	80	63	68
20375	Chhindwara	East Chhindwara	Amarwara	Gourpani	1126 PF	Bamboo	2016	Others				91.21	84.85	78.45	87	95	71	69.12	62.88	53	50
52124	Chhindwara	East Chhindwara	Amarwara	Bhajpani	1175 PF	Bamboo	2017	Others						94.5	80	95	82.92	90	85	81	71
52134	Chhindwara	East Chhindwara	Amarwara	Dulara	1186 PF	Misc	2017	Others						95.6	80	90	88	89.52	85	83	75
52135	Chhindwara	East Chhindwara	Amarwara	Dhasanwara	1178 PF	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 PF	Misc	2017	Compensatory Afforestation						95	76.16	95	90.24	94.33	94.24	94.46	94.15
52163	Chhindwara	East Chhindwara	Amarwara	Sarsdol	1230 PF	Misc	2017	Others						95.02	75.02	75.02	72	72.25	72	70.46	59.08
52164	Chhindwara	East Chhindwara	Amarwara	Kubri	1252 PF	Misc	2017	Others						89	90	95	80	78	77	76	70
52195	Chhindwara	East Chhindwara	Amarwara	Gadadaryaw	1169 PF	Misc	2017	Others						90.13	70.13	90.13	88	84	79.87	69	66.67
52196	Chhindwara	East Chhindwara	Amarwara	Putra	1180 PF	Misc	2017	Others						92	80	90	87.75	88	88	88	88
52211	Chhindwara	East Chhindwara	Amarwara	Karagatha	1142 PF	Misc	2017	Compensatory Afforestation						98.8	78	90	84	83	87.61	83.94	82.7
94510	Chhindwara	East Chhindwara	Amarwara	Sarijgani	1248 PF	Misc	2018	Working Plan Implementation								95	93	93.33	90	80	70
94511	Chhindwara	East Chhindwara	Amarwara	Sarijgani	1248 PF	Misc	2018	FDA (NAP)								95	90	94.02	78.05	65	55
94512	Chhindwara	East Chhindwara	Amarwara	Devangao	1208 PF	Misc	2018	FDA (NAP)								95	91.7	93.12	90.7	87	73.95
105362	Chhindwara	East Chhindwara	Amarwara	Chimouaa	1223 PF	Misc	2018	Compensatory Afforestation									100	90.18	86.4	82.24	
105363	Chhindwara	East Chhindwara	Amarwara	Karagatha	1142 PF	Misc	2018	Compensatory Afforestation									96	88	89.98	77.76	
105364	Chhindwara	East Chhindwara	Amarwara	Chimouaa	1224 PF	Misc	2018	Compensatory Afforestation									100	90.02	86.4	86.08	
105365	Chhindwara	East Chhindwara	Amarwara	Chimouaa	1224 PF	Misc	2018	Compensatory Afforestation									100	95.2	83.2	79.2	
105366	Chhindwara	East Chhindwara	Amarwara	Tendani	1222 PF	Misc	2018	Compensatory Afforestation									100	80	77.6	83.2	
105367	Chhindwara	East Chhindwara	Amarwara	Bagla	1216 PF	Misc	2018	Compensatory Afforestation									100	80	80	80	
105368	Chhindwara	East Chhindwara	Amarwara	Thavari	1173 PF	Misc	2018	Compensatory Afforestation									98	95.2	92.4	81.6	
105369	Chhindwara	East Chhindwara	Amarwara	Devangao	1208 PF	Misc	2018	Compensatory Afforestation									99.53	99	99.84	97.84	
105370	Chhindwara	East Chhindwara	Amarwara	Sejwara	1144 PF	Misc	2018	Working Plan Implementation									98.75	92.5	97	92.65	
105371	Chhindwara	East Chhindwara	Amarwara	Medki	1132 PF	Misc	2018	Working Plan Implementation									97.54	94	86	83	
105371	Chhindwara	East Chhindwara	Amarwara	Baralmari	1137 PF	Misc	2018	Working Plan Implementation									96.48	80	85	80	
105372	Chhindwara	East Chhindwara	Amarwara	Tinsai	1147 PF	Misc	2018	Working Plan Implementation									93	94	89.38	86	

Fig.1 Survival Report of Plantations

Division : East Chhindwara

Range : Chaurai

Area Type : Forest


Working Circle : Plantation Mgt

Scheme:	Working Implementation Plan	Plantation Category:	Teak
Maintenance Agency:	MPFD	Sanction Cost:	3560451
Actual Expenditure:	107100	Soil Type:	Forest Soils

Planted				
1	Teak	30000	12	2 X 2
2	Bamboo	2000	12	4 X 4
3	Kala Siras/ Kala Shirish	500	12	3 X 3
4	Aonla	500	12	3 X 3
5	Karanj/Kanji	500	12	3 X 3
6	Khamher/ Seevan	500	12	3 X 3
7	Arjun	1000	12	3 X 3

Evaluation Details

Type	Period	Status	Evaluated By	Evaluation Date	Survival (%)
Post-Monsoon	Oct-2015	Done	Mr. Vinay Kumar Meshram RO Chourai	15-Oct-2015	91.80
Pre-Monsoon	May-2016	Done	vinay kumar meshram ro chourai	2-Jun-2016	81.31
Post-Monsoon	Oct-2016	Done	Vinay Kumar Meshram RO Chourai	2-Oct-2016	84.19
Pre-Monsoon	May-2017	Done	Lalji Ulkey	6-May-2017	80.74



KML/KMZ फोटो




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 .

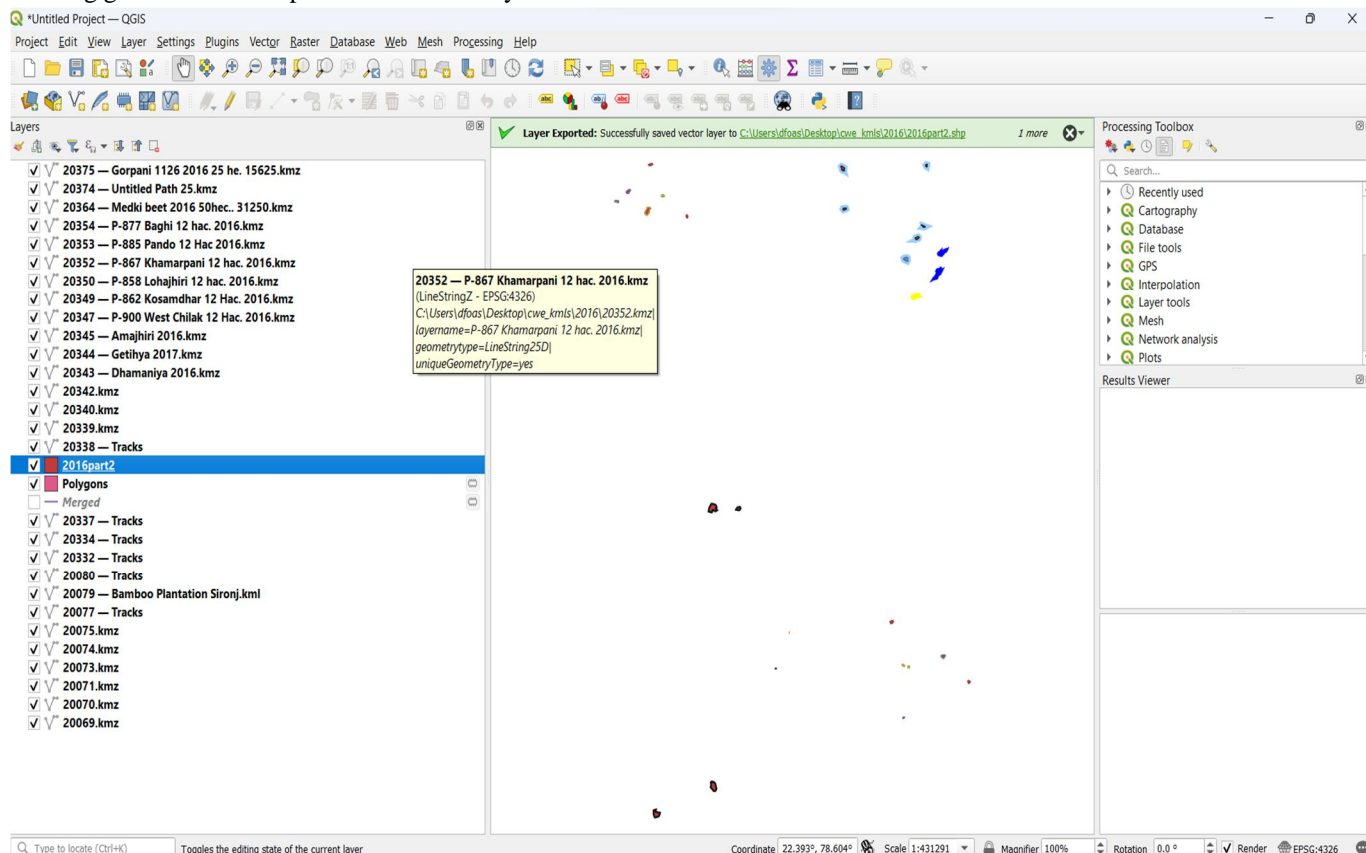


Fig.3 KML files Processing in QGIS

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

	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":"MultiPolygon
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":"MultiPolygon
8	7	19283	127.4521552	-0.1920846053	0.09566752602	-0.0601483986	0.1434838067	("type":"MultiPolygon
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	000000000000000000	19391	113.1864937	-0.1587692604	0.09479481155	-0.04193772272	0.1421676767	("type":"Polygon","cc
12	000000000000000000	19392	61.75641322	-0.05044091273	0.04086791998	-0.01983820533	0.06129367215	("type":"Polygon","cc
13	000000000000000000	19398	87.96906089	-0.1347571117	0.07816838872	-0.040547038	0.1172323646	("type":"Polygon","cc
14	000000000000000000	19400	124.7826303	-0.1357711431	0.1119769377	-0.05095998663	0.1679373111	("type":"Polygon","cc
15	000000000000000000	19401	151.0403436	-0.1629308578	0.1140908065	-0.05349684247	0.1711134672	("type":"Polygon","cc
16	000000000000000000	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

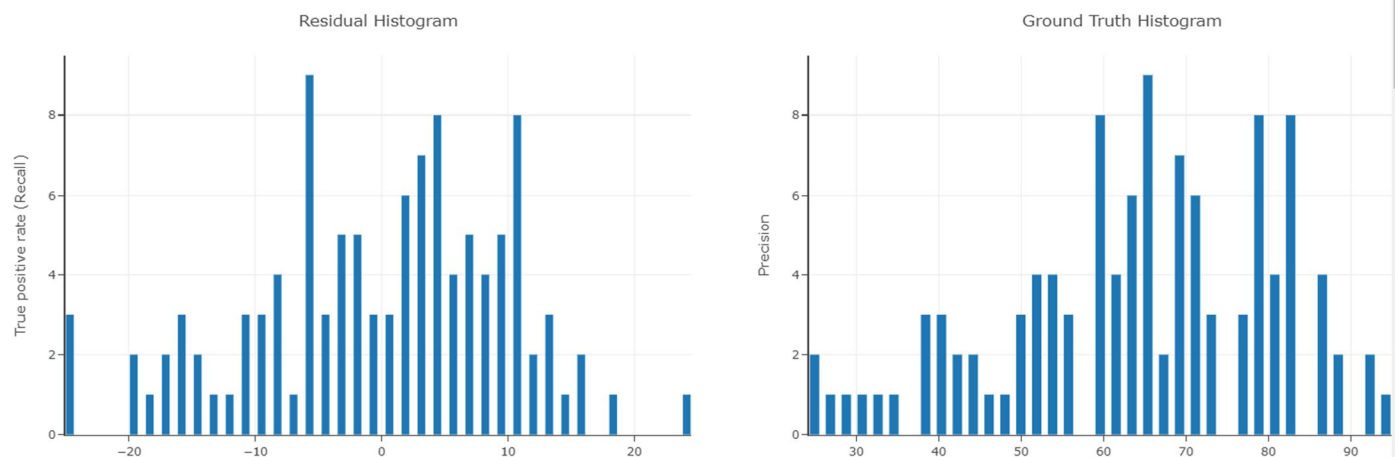
Our dataset, housed within Google Sheets, encompassed 112 unique plantation records, each denoted by a Plantation ID. Each record detailed the slopes of satellite-derived indices, serving as predictive features for plantation survival rates. Using the "Simple ML for Sheets" extension, we streamlined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



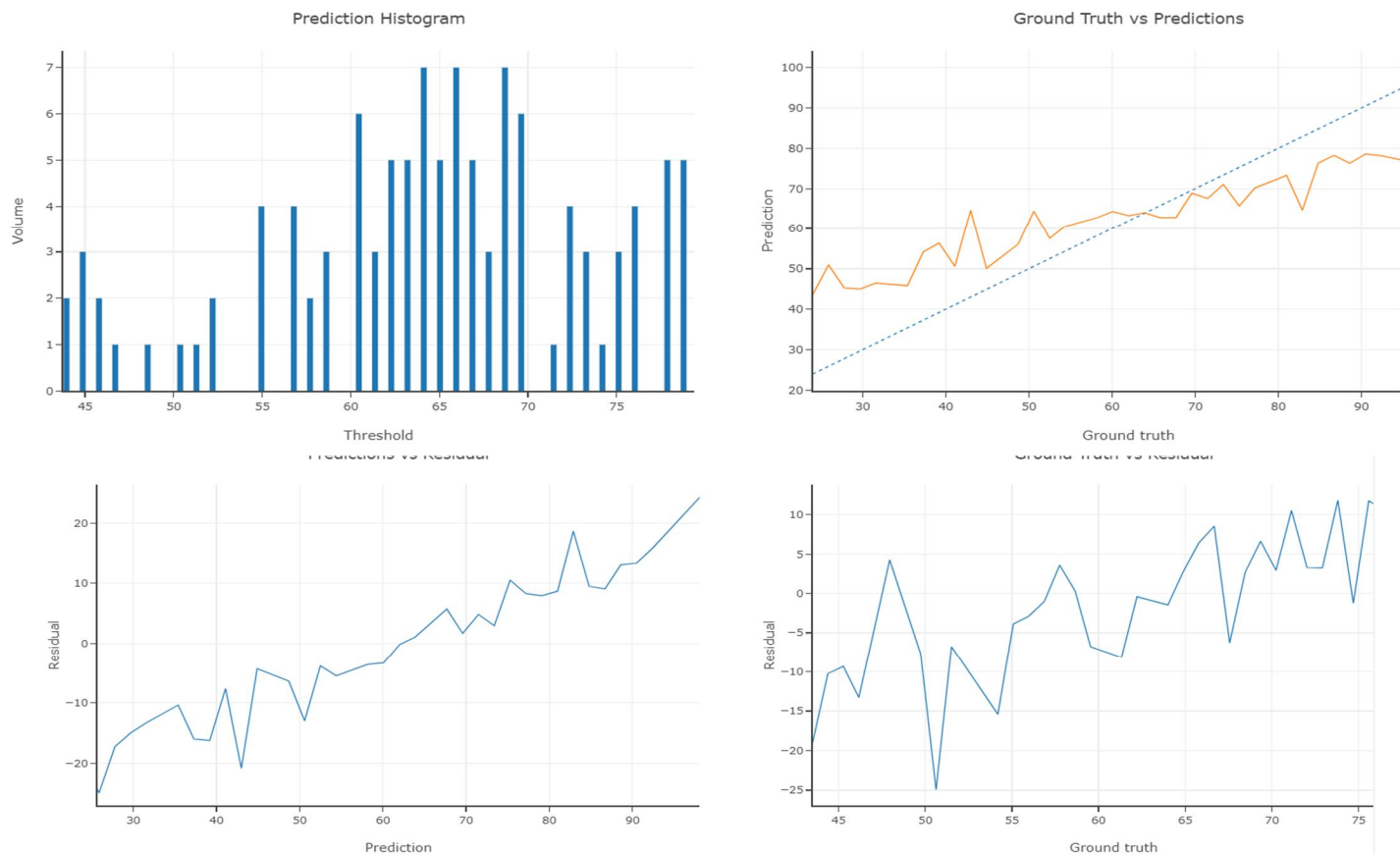


Fig.6 Model Evaluation Report

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 only 2015 to 2018. 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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