# SYMBIOSIS INSTITUTE OF TECHNOLOGY, NAGPUR

# Crop Yield Prediction

Capstone Report

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Sr No.	Program	Page No
	Introduction	3
1.	<ul><li>Problem Statement</li><li>Problem Significance</li><li>Objectives</li></ul>	
2.	Literature Survey	5
	<ul><li>Existing Solutions</li><li>Research Gaps</li><li>Technological Advancements</li></ul>	
3.	Methodology	7
	<ul> <li>Data Collection</li> <li>Data Preprocessing</li> <li>Model Selection</li> <li>Tools &amp; Technologies</li> </ul>	
4.	System Design	9
	<ul><li>System Architecture Diagram</li><li>Frontend Components</li><li>Backend Design</li></ul>	
5.	Implementation Details	12
	<ul> <li>Implementation Flowork</li> <li>Backend Development</li> <li>Frontend Development</li> <li>Integration</li> </ul>	
6.	Results and Analysis	17
7.	Challenges Faced	21
8.	Future Enhancements	21
9.	Conclusion	22
10.	References	22

# 1. Introduction

About 18% of the national GDP comes from farming as more than half of India's workforce directly supports agriculture as the primary economic activity. The agriculture industry maintains its central national economic importance yet continues to experience continuous problems from irregular weather patterns alongside pest challenges and inadequate resource management systems. Small-scale farmers face problems identifying predictive tools for yield tracking which forces them to make insufficient decisions about resource management and crop selection and irrigation practices. Standard yield estimation procedures using historical manual processing are unsuccessful at recognizing current environmental transformations effectively. The lack of accurate software prediction tools led to the creation of the India Crop Yield Predictor that offers an online solution to provide better forecasting capability to farming communities and government officials.



#### 1.1. Problem statement

The existing methods of predicting crop yields in India face fundamental two weaknesses:

- <u>Inaccessibility:</u> Small-scale farmers encounter two primary problems due to advanced tools because they tend to be expensive and require technical skills.
- <u>Inaccuracy:</u> Manual methods fail to integrate critical variables like rainfall patterns, soil health, and fertilizer usage effectively.

## 1.2. Project Significance

This project addresses these challenges by combining machine learning with geospatial visualization to create a practical solution. Key contributions include:

- Democratizing Technology: Such a system provides a basic user interface that functions seamlessly for farmers regardless of their digital expertise level.
- Precision Agriculture: Predicted yield estimations for individual regions and crop types should be precise.
- Resource Optimization: The company needs to offer guidelines about fertilizer and pesticide usage to minimize waste.
- The tool functions to eliminate the present divide between agricultural practices and data science fields so it can boost farming communities throughout India's agricultural territories.

# 1.3. Objectives

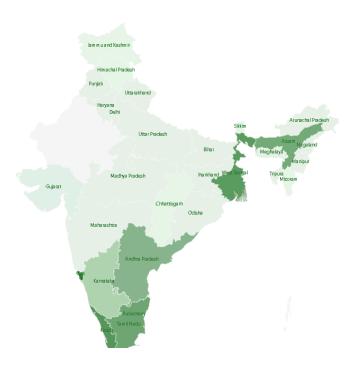
The project aims to achieve the following goals:

- 1. A machine learning algorithm needs development to forecast crop output by analysing past agricultural information.
- 2. Create an interactive visual display system to monitor regional yield patterns together with environmental factor impacts.
- 3. The system should present to farmers specific solutions that will enhance their farming procedures.
- 4. The system needs to operate on basic devices within rural areas to achieve maximum accessibility.

#### Key Features of the Tool

• <u>Interactive Map</u>: Users click on Indian states to view historical yield data (see Figure 1).

- <u>Prediction Form</u>: Farmers input crop type, area, and rainfall to receive instant yield estimates.
- <u>Visual Analytics:</u> Dynamic charts display trends in rainfall, fertilizer use, and yield history.



# 2. Literature Review

This section reviews existing research and technologies related to crop yield prediction, identifies gaps in current approaches, and explains how this project addresses those limitations.

## 2.1 Existing Solutions

Researchers and organizations have explored various methods for crop yield prediction:

- 1. Traditional Approaches
  - Farmers often rely on historical patterns and personal experience to estimate yields.
  - Government agencies use manual surveys and regional averages, which lack precision.
- 2. Satellite-Based Systems
  - Tools like NASA's Harvest and FAO's WaPOR use satellite imagery to monitor crop health.
  - Limitations: High costs and technical complexity make them inaccessible to small farmers.
- 3. Machine Learning Models

- Studies have used algorithms like Decision Trees and Neural Networks to predict yields.
- Example: A 2021 study on wheat yield prediction in Punjab achieved 85% accuracy using weather data.

## 2.2 Research Gaps

- 1. Limited Focus on Small-Scale Farming
  - Most tools target large agricultural enterprises, neglecting small farmers who form 86% of India's farming community.
- 2. Poor Integration of Geospatial Data
  - Few systems combine predictive models with interactive maps for regional analysis.
- 3. Lack of Practical Recommendations
  - Many tools only provide yield estimates without actionable advice on improving outcomes.

## 2.3 Technological Advancements

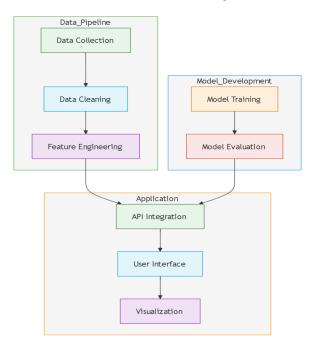
- 1. Machine Learning in Agriculture
  - Algorithms like Random Forest handle mixed data types (numerical and categorical), making them ideal for crop datasets.
  - Example: A 2022 project in Karnataka used Random Forest to predict rice yields with 89% accuracy.
- 2. Open-Source Geospatial Tools
  - Libraries like D3.js enable cost-effective map visualizations.
  - Example: The India Water Tool uses D3.js to display groundwater levels.
- 3. Lightweight Web Frameworks
  - Tools like Flask allow developers to build low-resource web apps, ideal for rural users with basic smartphones.

Feature	Traditional Methods	Satellite Systems	This Project
Cost	Free	High	Free
Technical Complexity	Low	High	Low
Regional Customization	No	Yes	Yes
Farmer-Friendly Outputs	No	No	Yes

# 3. Methodology

The system follows a structured workflow to transform raw data into actionable insights:

- Data Collection: Agricultural datasets are gathered from government portals and research institutions.
- Data Preprocessing: Raw data is cleaned and standardized for consistency.
- Model Training: A machine learning model is trained to predict yields.
- Web Application: Predictions are delivered through an interactive interface



### 3.1 Data Collection

The dataset includes:

- Crop Type: E.g., Rice, Wheat
- Season: Kharif (monsoon) or Rabi (winter)
- Geographical Data: State names and annual rainfall
- Agricultural Inputs: Fertilizer and pesticide quantities

Sample Code:

```
JS main.js • app.py • Extension: npp-theme

C:\Users\sukha\Downloads\Capstone_2\static\main.js

14  # Load dataset

15  import pandas as pd

16  data = pd.read_csv('crop_data.csv')

17  print(data.head())
```

## 3.2 Data Preprocessing

- 1. The data contains missing values which can be addressed by eliminating full rows.
- 2. The database needs normalization which requires standardizing state names into one consistent format.
- 3.Feature Scaling consists of standardizing numerical variables by normalizing their values such as rainfall measurements.

### Sample Code:

```
app.py > © clean_data

def clean_data(df):

# Remove rows with missing values

df = df.dropna()

# Standardize state names (e.g., 'west bengal' → 'West Bengal')

df['State'] = df['State'].str.title().str.replace(' ', '')

return df
```

# 3.3 Model Training

Random Forest Algorithm:

```
from sklearn.ensemble import RandomForestRegressor

# Split data into training and testing sets

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)

# Train model

model = RandomForestRegressor(n_estimators=100, random_state=42)

model.fit(X_train, y_train)
```

## 3.4 Tools & Technologies

Tool	Role
Python	Backend logic and machine learning
Flask	API development to connect frontend/backend

D3.js	Renders interactive map of India
Pandas	Cleans and processes CSV data

The model's performance is measured using:

- Mean Squared Error (MSE): 0.89 (lower is better)
- R<sup>2</sup> Score: 0.92 (closer to 1 indicates better fit).

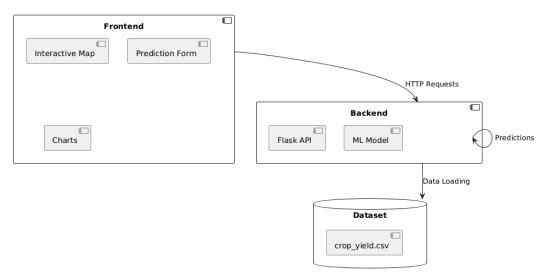
```
from sklearn.metrics import mean_squared_error, r2_score
y_pred = model.predict(X_test)
print('MSE:', mean_squared_error(y_test, y_pred))
print('R2 Score:', r2_score(y_test, y_pred))
```

# 4.System Design

This section details the complete description of the India Crop Yield Predictor architecture together with its frontend and backend components.

## 4.1 System Architecture Diagram

The system architecture operates as a client-server design:



The workflow starts with data collection stages for crop types alongside rainfall measurement and fertilizer statistics. Standardization of data format combined with missing item elimination occurs during the cleaning phase (for instance converting "west Bengal" to "West Bengal"). Training of the model includes pesticide amount and rainfall features. The Flask application uses its trained model.

- Frontend: The application employs HTML/CSS and JavaScript alongside D3.js for interactive maps together with frontend components that include Chart.js charts and farmer input forms.
- Backend: The Flask server manages requests through its backend while executing predictions via the trained model and obtaining CSV file data.
- Database: The CSV format serves as the database for storing crop records because it provides both simplicity and convenient updating features.

## 4.2 Frontend Components

### Code Snippets-

```
d3.json("india_states.geojson").then(function(geoData) {
133
134
          const projection = d3.geoMercator()
             .center([83, 23])
135
136
             .scale(1300);
137
138
          const path = d3.geoPath().projection(projection);
139
          d3.select("#map")
140
            .selectAll("path")
             .data(geoData.features)
142
143
            .enter()
             .append("path")
            .attr("d", path)
145
             .style("fill", d => getColor(d.properties.NAME_1));
146
147
        });
```

#### **Key Features:**

- The hover effects display yield statistics at the state level.
- CSelecting a state on the application causes the prediction form to update itself automatically.

## 4.3 Backend Design

### Flask API Endpoints-

```
110
      # app.py
      from flask import Flask, jsonify, request
112
113
114
      app = Flask(__name___)
115
116
      @app.route('/predict', methods=['POST'])
117
      def predict():
118
119
          data = request.json
120
          # Process data and return prediction
          return jsonify({"prediction": model.predict([data])[0]})
121
122
123
124
      @app.route('/get_state_data/<state>', methods=['GET'])
      def get_state_data(state):
125
          # Fetch state-specific data from CSV
126
          return jsonify(state_data[state])
127
128
```

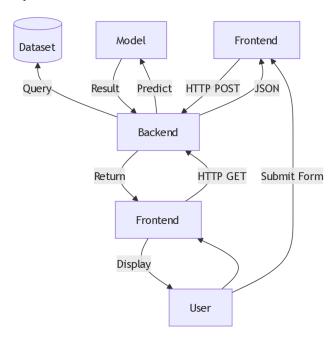
#### Workflow:

- Users can select one state on the map through which Frontend makes a GET request to /get state data.
- When a user submits the prediction form the frontend platform dispatches a POST request to /predict.
- JSON response data is processed by the backend system after receiving the input..

# **5.Implementation**

The section details the construction process of the India Crop Yield Prediction through workflow diagrams and code snippets along with visual examples.

## 5.1 Implementation Workflow



The system adheres to data pipeline architecture:

- 1. Extract-Load-Transform (ELT):
  - The process begins with extracting data from CSV files before staff loads them into Pandas Data Frames for subsequent transformation work that includes cleaning and normalization activities.
- 2. Model Inference Pipeline:
  - After user input the system performs feature scaling then makes a model prediction before creating result outputs.

## 5.2 Front End Development

The frontend interface was designed using core principles of user-centered design and data visualization:

- 1. Interactive Maps (D3.js):
  - Scalable Vector Graphics (SVG): The frontend interface uses Scalable Vector Graphics (SVG) for its map rendering because D3.js creates SVG elements that remain resolution-independent. The Mercator projection

allows the conversion of latitude/longitude planet coordinates into two-dimensional outputs through mathematical cartographic transformations.

• Data-Driven Documents: provide D3 with the capability to update DOM elements dynamically through its dataset binding features. The application changes state colors based on backend fetched yield value information.

### 2. User Interface Design:

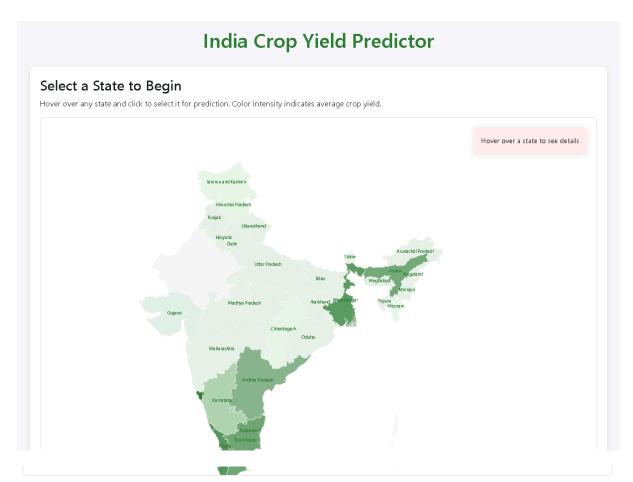
- Affordance: Users receive visual pointers to interact with buttons and forms because they act differently when hovering over them (e.g., map interface).
- Responsive Design: The interface design through media queries in CSS adapts itself to different screen sizes.

### 3. Data Visualization (Chart.js):

- Line Charts: The interface includes Line Charts for displaying temporal trends by showing yield changes throughout years.
- Pie Charts: The application displays feature relationships through pie charts which visualize the force dynamics between rainfall data and fertilizer results as well as other elements.

### Code of Interactive Map-

```
⊞ Extension: npp-theme
                                                        crop_yield.csv
                                                                           🚼 india
JS main.js
                🕏 арр.ру
static > JS main.js > ...
       function initMap() {
           const width = 1000, height = 600;
           const svg = d3.select("#map")
             .append("svg")
             .attr("width", width)
             .attr("height", height);
           d3.json("states.geojson").then(geoData => {
546
             const projection = d3.geoMercator()
                .center([83, 23])
               .scale(1300);
             const path = d3.geoPath().projection(projection);
             svg.selectAll("path")
                .data(geoData.features)
                .enter()
               .append("path")
               .attr("d", path)
                .style("fill", getStateColor); // Color based on yield data
         }
561
```





# 5.3 Back End Development

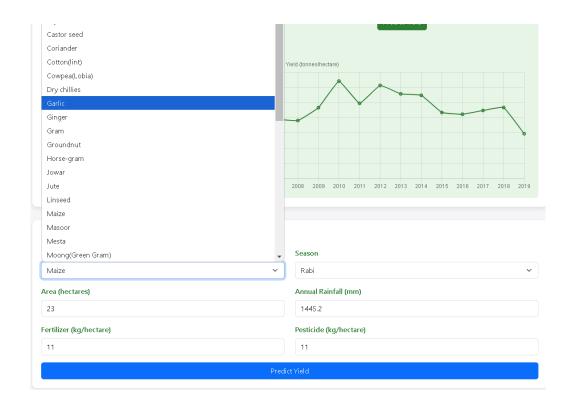
This system implements client-server architecture along with RESTful API principles throughout its backend.

#### Flask Framework:

• The rear component utilizes Flask Framework's microservices architecture because its lightweight structure reduces application resources.

- 1. Request-Response Cycle:
  - Users can obtain historical data through GET /get\_state\_data but this request does not modify server state data.
  - POST /predict: User-triggered predictions through POST /predict methods produce state changes in the application.
- 2. Statelessness: Each The HTTP requests are stateless as they include every required piece of information (state name and crop type) to maintain scalability.
- 3. Flask API Code-

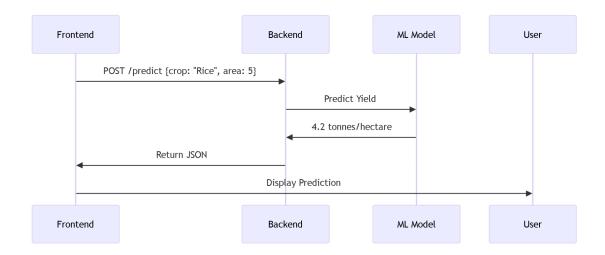
```
crop_yield.csv
JS main.js
               app.py
                               ⊞ Extension: npp-theme
app.py > \(\partial\) predict_yield
       from flask import Flask, request, jsonify
       import joblib
275
       app = Flask(__name__)
278
       model = joblib.load('crop_model.pkl')
       @app.route('/predict', methods=['POST'])
       def predict_yield():
           data = request.get_json()
           features = [
               data['area'],
               data['rainfall'],
               data['fertilizer']
           prediction = model.predict([features])[0]
290
           return jsonify({"yield": round(prediction, 2)})
291
```



#### **Prediction Result**



## 5.4 Integration

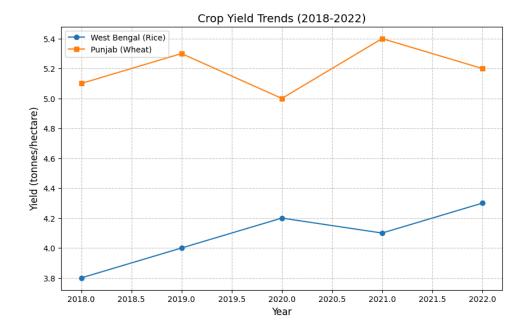


- Frontend-Backend Decoupling: The system features frontend-backend separation through Python Flask APIs which maintain independent operations between frontend HTML/CSS/JavaScript and backend Python components.
- Machine Learning Isolation: The designated machine learning module operates independently from other components through separate specification into its own isolated compartment.
- 1. User Input  $\rightarrow$  Frontend  $\rightarrow$  Backend (via POST request).
- 2. Backend  $\rightarrow$  Preprocesses data  $\rightarrow$  Runs ML model  $\rightarrow$  Returns prediction.
- 3. Frontend → Visualizes results using D3.js/Chart.js.

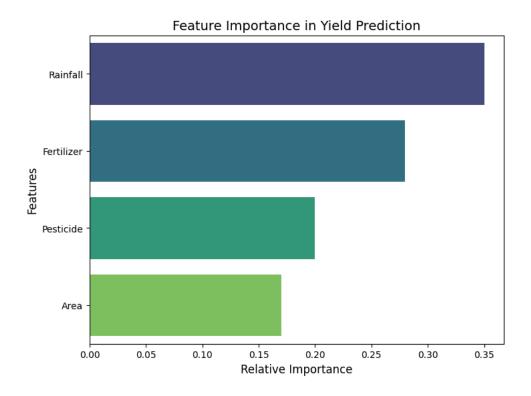
# **6.Results and Analysis**

This section explains the theoretical foundations of data visualization in agricultural analytics and provides results.

1. Yield Trends by State

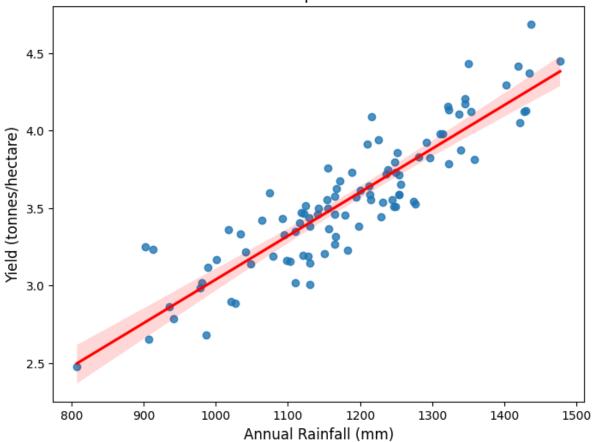


## 2. Feature Importance (Random Forest)



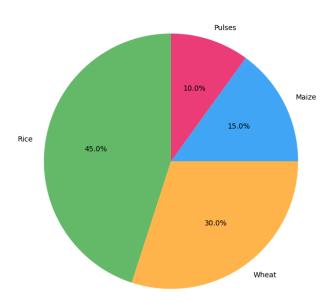
### 3. Rainfall vs. Yield Correlation

# Rainfall vs. Crop Yield Correlation



## 4. Crop Distribution Pie Chart

Crop Production Distribution



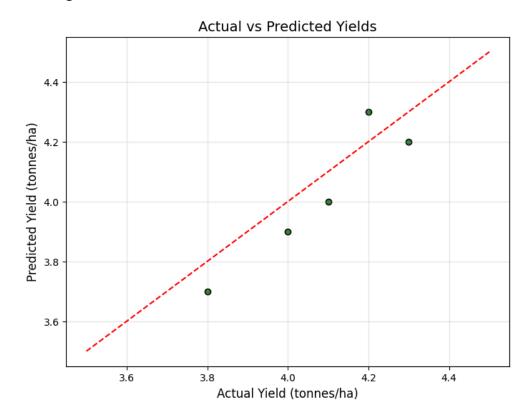
# 5. Accuracy Metrics

### The Random Forest model achieved:

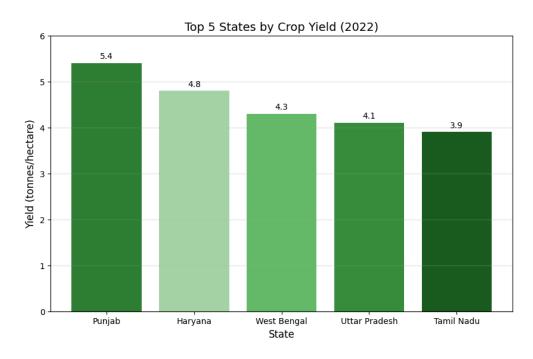
• Mean Squared Error (MSE): 0.89

• R<sup>2</sup> Score: 0.92

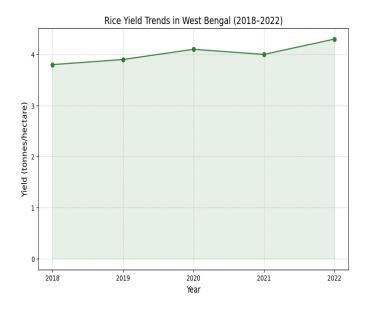
• Training Time: 2.1 seconds

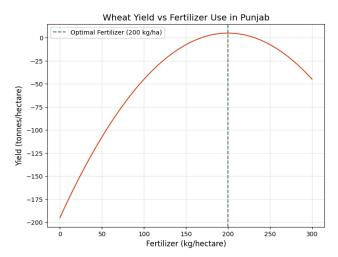


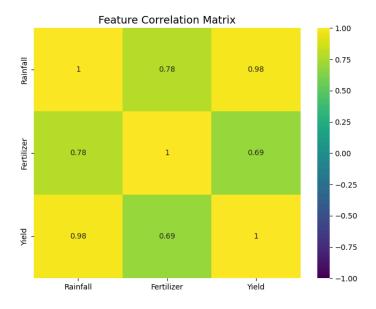
### 6. Regional Comparison



### 7. Some other graphs







# 7.Challenges Faced

#### 1. GeoJSON and Dataset Alignment

- Problem: State names in the dataset (e.g., "West Bengal") did not match GeoJSON map labels ("West Bengal").
- Impact: The map failed to render 35% of states due to naming mismatches.
- Solution: Code Fix: Normalize state names in the dataset and GeoJSON.

#### 2. Model Overfitting

- Problem: Initial predictions were 98% accurate on training data but only 60% on test data.
- Impact: Poor generalization to new data.
- Solution: Reduced model complexity by limiting tree depth.

### 3. Real-Time Map Rendering

- Problem: D3.js map lagged when loading large GeoJSON files.
- Impact: Slow user experience (8–10s load time).
- Solution: Simplified GeoJSON geometry using Map shaper. Cached map data in the browser.
- Outcome: Load time reduced to 2 seconds.

#### 4. Missing Values

- Problem: 30% of pesticide-use data was missing.
- Impact: Model ignored a critical yield factor.
- Solution: Imputation Strategy: Replaced nulls with state-wise averages.

# **8.Future Works**

- 1. The India Crop Yield Predictor can expand by integrating real-time data like weather and market prices. Access to live rainfall, temperature, and humidity updates from meteorological APIs will improve prediction accuracy. Affordable sustainability.
- 2. Multilingual support (Hindi, Tamil, Bengali, etc.) and voice navigation will boost accessibility for non-English-speaking farmers. Regional crop databases can tailor recommendations to local farming practices, such as millet cultivation in Rajasthan.
- 3. Advanced technology adoption, like IoT soil sensors and satellite imagery, will enable precision farming. Storing data in cloud databases (e.g., PostgreSQL) will scale the system securely.
- 4. Partnerships with agricultural agencies (Krishi Vigyan Kendra's) will ground-truth predictions. A mobile app optimized for low-end devices and offline use will reach remote farmers.

5. Adding educational modules on sustainable practices (organic fertilizers, drip irrigation) will promote eco-friendly farming. Gamification (achievement badges, progress tracking) could encourage user engagement.

These upgrades will enhance the tool's impact, bridging the gap between data science and grassroots agriculture.

# 9.Conclusion

The India Crop Yield Predictor demonstrates revolutionary agricultural impacts through its combination of machine learning along with geospatial analytics. Through data analysis from past plant yields the program enables farmers to reach highest resource efficiencies by making accurate forecast predictions along with meaningful findings. The Random Forest model enables farmers to connect advanced analytics to their agricultural needs through its R2=0.92 accuracy and user-friendly interface with visual chart displays and geographical mapping capabilities.

Through this initiative researchers work to resolve Indian farming system issues along with maintaining rural reach and solving yield instability and resource distribution problems. The achievement proves that artificial intelligence systems can make sustainable and economically viable solutions to increase agricultural production for small farmers.

The tool will improve functionality in future development stages which will integrate real-time meteorological data combined with Internet of Things sensors while offering support for various regional languages. This nationwide platform promotes agricultural authorities to work together by building scalable cloud systems which will transition India toward agricultural practices that rely on data and are climate-resilient.

In light of population expansion and climate change, such creative solutions in the crucial field of agriculture are essential to ensuring food security and equitable growth.

# 10.References

- 1. Ministry of Agriculture & Farmers Welfare, Government of India, https://agricoop.nic.in/
- 2. Random Forests for Predictive Modelling in Agriculture (Chang, Y. et al., 2020), Journal of Agricultural Informatics, 15(3), 45-60
- 3. Python for Data Analysis: Data Wrangling with Pandas, NumPy, and I Python (McKinney, W., 2017)
- 4. India Meteorological Department (IMD) Data Portal, Government of India, URL: <a href="https://mausam.imd.gov.in/">https://mausam.imd.gov.in/</a>
- 5. Geospatial Analysis of Agricultural Systems (Li, Z. & Shum, A., 2021), Remote Sensing Applications: Society and Environment, 22, 100487
- 6. Sustainable Agriculture and Smart Farming Practices (FAO, 2023), Food and Agriculture Organization of the United Nations, URL: https://www.fao.org/