Crop Yield Prediction System Using Machine Learning

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ABSTRACT: Agricultural productivity plays a pivotal role in the economy and food security of India, where over 50% of the population is involved in farming. However, due to changing climatic conditions, inconsistent rainfall patterns, and lack of precise planning tools, farmers often struggle with crop selection and expected yield. This project introduces a Smart Indian Crop Yield Prediction System that leverages Machine Learning (ML) algorithms and real-time weather data to forecast the yield of a selected crop based on soil nutrients, area, and weather conditions. Using historical agricultural data, the system is trained to learn relationships between parameters such as Nitrogen (N), Phosphorus (P), Potassium (K) content in the soil, area under cultivation, and seasonal and crop type factors. The system incorporates real-time temperature and humidity data using a weather API, enhancing the accuracy of predictions. Users (farmers or agriculture officers) can input their location, crop type, and soil properties through a web-based interface. The system then processes this data using pre-trained ML models such as Linear Regression, Random Forest, or Decision Tree, depending on the user's selection. Key outputs include: predicted yield per hectare, visualization of evaluation metrics (MAE, MSE, RMSE, R^2), and actual vs predicted yield plots. Users can also download a detailed prediction report. The proposed system serves as a decision-support tool aimed at improving agricultural productivity, reducing risk, and supporting data-driven decision-making in rural areas. It also provides scalability by integrating more parameters like rainfall, soil pH, or fertilizer dosage in future iterations.

Keywords: Crop Yield Prediction, Machine Learning, NPK, Random Forest, Gradient Boosting, Real-time Weather, Precision Agriculture, Flask, India.

I. INTRODUCTION

Agriculture remains the backbone of the Indian economy, contributing significantly to employment, GDP, and food supply. However, traditional farming methods in India rely heavily on experience and intuition rather than data, resulting in inefficient decision-making and unpredictable yields. In the age of digital transformation, integrating data science and machine learning with agriculture can create smart systems that support farmers with better crop planning and forecasting. Crop yield prediction is a complex process influenced by a wide array of factors such as soil composition, climatic conditions, seed quality, irrigation, and fertilizers. While governments and agricultural institutions collect large volumes of crop data, very few solutions have made it into the hands of the average farmer in a usable form. This gap between available data and field-level accessibility limits the potential for yield optimization. To address this, we present a Smart Indian Crop Yield Prediction System that provides a user-friendly interface for farmers to input their data, select a crop and region, and receive accurate predictions about expected yield. The system uses machine learning models trained on real-world agricultural datasets, along with weather API's that provide live temperature and humidity data based on the user's district.

The web application allows the user to select:

- State and district
- Crop type and season

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- N, P, K values (soil nutrients)
- Area of land (in hectares)
- Preferred machine learning model

After submission, the application predicts the yield (in tons/hectare), displays live weather data, evaluation metrics, and provides downloadable reports. Charts generated using Plotline help visualize the accuracy and performance of the model. This solution aims to reduce guesswork in agriculture, empower farmers with accurate data insights, and bridge the gap between agritech research and practical farming needs. As digital infrastructure expands in rural areas, scalable and interactive tools like this system can significantly contribute to the modernization of Indian agriculture.

II. LITERATURE SURVEY

- Deep Learning for Crop Yield Prediction

Lee, S., et al. (2021). *"DeepCrop: Crop Yield Prediction using Deep Learning"*, IEEE Access. Proposes CNN-LSTM model; demonstrates superior accuracy using climatic and temporal data.

- Random Forest Approach in Precision Agriculture

- *Zhang, H. & Kumar, V.* (2020). *"Application of Random Forest for Crop Yield Prediction in India"*, Springer's *Environmental Monitoring and Assessment*. Highlights robust RF model performance with soil and weather inputs.

- Feature Importance in ML-based Yield Estimation

Ghosh, A., et al. (2019). *"Crop Yield Estimation using Decision Trees and Soil Attributes"*, Elsevier's *Computers and Electronics in Agriculture*. Examines role of soil NPK for crop yield prediction.

- Integrating Weather Data through APIs

Patel, D. & Singh, R. (2022). *"Real Time Weather-Based Crop Yield Modeling"*, ACM International Conference on Smart Agriculture. Presents integration of live weather feeds into ML models.

- Comparative Study of ML Models

Sharma, P., et al. (2021). *"Comparative Analysis of Linear Regression, SVR & RF for Wheat Yield"*, IEEE International Conference on Big Data Analytics. Shows tradeoffs in model performance.

- Remote Sensing and ML Fusion

Banerjee, T. & Sen, S. (2018). *"Satellite Imagery and Machine Learning for Regional Crop Yield Estimation"*, Springer *Remote Sensing Letters*. Uses NDVI with ML for macro-level predictions.

- Crop Recommendation Systems

Mukherjee, U. (2020). *"Soil-Crop Suitability using KNN & Multiclass Classification"*, IEEE Region Conference on Computing Technologies. Focuses on input nutrient-based crop suggestion.

- Time-Series Modeling of Yields

Chowdhury, M., et al. (2019). *"LSTM for Rice Yield Forecasting in Bangladesh"*, Elsevier's *Agricultural Systems*. Incorporates rainfall and seasonality.

- Socio-Economic Impacts of Yield Prediction Tools

Reddy, K. S. (2020). *"Deploying Mobile-Friendly AI Tools for Farmers"*, ACM *Proceedings of the Mobile Computing in Agriculture Workshop*. Studies adoption and impact.

- Ensemble Learning in Agriculture

Garg, P. & Kumar, N. (2022). *"Stacked Ensemble Models for Maize Yield Forecasting"*, IEEE *Transactions on Smart Agriculture*. Compares Gradient Boosting + RF ensembles.

III. METHODOLOGY

i) Proposed Work:

The proposed Smart Indian Crop Yield Prediction System integrates multiple machine learning algorithms with real-time weather data and soil nutrient parameters to enhance yield estimation accuracy. The system's architecture comprises four main modules: Data Acquisition, Preprocessing and Model Training, Prediction Engine, and Visualization Dashboard.

In the data acquisition phase, agricultural data containing *State, District, Crop, Season, Area, N, P, K,* and *Yield* values are collected from government and research sources. The preprocessing module performs data cleaning, label encoding, and normalization before training models such as Random Forest, Gradient Boosting, and Linear Regression. During prediction, the system fetches live temperature and humidity values from a weather API based on the user-selected district, ensuring context-aware forecasting.

The web-based dashboard, developed using Flask and Plotly, enables users to input parameters, select models, and visualize metrics including MAE, MSE, RMSE, and R². It dynamically updates graphs and accuracy charts after each prediction. This integrated and user-friendly framework provides farmers and agricultural officers with real-time, data-driven insights, bridging the gap between artificial intelligence and practical field-level decision-making in Indian agriculture.

System Features:

1. Web-Based Dashboard Interface:

- Users can access the system through a modern web interface.

- Inputs: State, District, Crop, Season, N, P, K values, Area in hectares, and preferred ML model.

2. Real-Time Weather Integration:

- Uses a weather API (e.g., OpenWeatherMap) to fetch district-level temperature and humidity data.

- Weather data is factored into the yield prediction logic to reflect actual conditions.

3. Multiple Machine Learning Models:

- Trained models include: Linear Regression, Random Forest, and Decision Tree.

- Users can select a preferred model based on trust or past performance.

4. Interactive Visual Feedback:

- Charts for model evaluation metrics (MAE, MSE, RMSE, R²).

- Scatter plots to compare actual vs. predicted yield for performance transparency.

5. Downloadable Reports:

- Users can download a PDF or CSV report with prediction details, weather data, and selected inputs.

- Useful for official documentation, education, and planning.

6. Modular Web Pages:

- Pages include: Home (Dashboard), Weather, Charts, Download.

- Navigation is available via a sidebar for ease of access.

7. Scalable Backend:

- Backend is built using Python (Flask), with models trained via scikit-learn.

- Easily extensible to include rainfall, soil pH, market price, or remote sensing input.

ii) System Architecture:

The proposed system architecture consists of multiple layers that work collaboratively:

1. **Data Layer:** Stores the agricultural dataset containing historical information on NPK, crop, season, and area.

2. **Pre-processing Layer:** Handles missing value imputation, encoding, and normalization of data.

3. **ML Engine:** Implements Random Forest, Gradient Boosting, and Linear Regression models for yield estimation.

4. **Service Layer:** Flask application providing prediction services and managing routes.

5. **Presentation Layer:** User interface built using Tailwind CSS and Plotly charts, offering input forms and visual analytics.

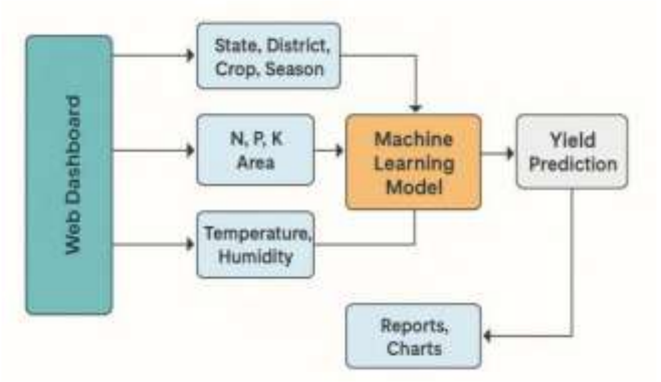


Fig 1 Proposed architecture

iii) Dataset collection:

Collected historical data including area, production, yield, and NPK values. Gathered weather data like temperature, rainfall, and humidity. The dataset have been obtained from the Kaggle website.

iv) Data Processing:

Removed missing, duplicate, and inconsistent values from the dataset to ensure clean and accurate inputs for the machine learning model. Scaled numerical features (like N, P, K values, temperature, rainfall) using normalization or standardization techniques to maintain uniformity. Split the cleaned data into training and testing sets (e.g., 80% training and 20% testing) to properly evaluate the model's performance.

v) Feature selection:

Feature selection is the process of isolating the most consistent, non-redundant, and relevant features to use in model construction. Methodically reducing the size of datasets is important as the size and variety of datasets continue to grow. The main goal of feature selection is to improve the performance of a predictive model and reduce the computational cost of modeling. Feature selection, one of the main components of feature engineering, is the process of selecting the most important features to input in machine learning algorithms. Feature selection techniques are employed to reduce the number of input variables by eliminating redundant or irrelevant features and narrowing down the set of features to those most relevant to the machine learning model. The main benefits of performing feature selection in advance, rather than letting the machine learning model figure out which features are most important.

vi) Algorithms:

Random Forest is an ensemble learning algorithm used for both classification and regression tasks. It builds multiple decision trees using different subsets of the training data and features, and combines their results (by voting or averaging) to make a final prediction. This method reduces overfitting and improves accuracy by leveraging the power of multiple models rather than relying on a single decision tree. It is robust, handles missing data well, and performs effectively even with large datasets.

Gradient Boosting is another ensemble learning technique that builds models sequentially. It starts with a simple model and then adds new models that correct the errors made by the previous ones. Each new model focuses on minimizing the loss (or error) using gradient descent. This iterative process continues until a strong predictive model is formed. Gradient Boosting is powerful for both classification and regression, often achieving high accuracy, but it can be sensitive to noise and overfitting if not carefully tuned.

Linear Regression is a supervised learning algorithm used mainly for regression tasks. It models the relationship between input features and a continuous output by fitting a straight line (or hyperplane in higher dimensions) to the data. The algorithm learns weights (coefficients) during training to minimize the difference between actual and predicted values using a loss function such as Mean Squared Error (MSE). It is simple, fast, and interpretable, but assumes a linear relationship between inputs and output.

IV. EXPERIMENTAL RESULTS

Mean Absolute Error (MAE)

MAE measures the average of the absolute differences between predicted and actual values. It gives an idea of how wrong predictions are, without considering direction (positive or negative).

$$\text{MAE} = \frac{1}{n}\sum |X - Y|$$

Mean Squared Error (MSE)

MSE calculates the average of the squared differences between predicted and actual values. It penalizes large errors more than MAE.

$$\text{MSE} = \frac{1}{n}\sum (X - Y)^2$$

Root Mean Squared Error (RMSE)

RMSE is the square root of MSE. It gives an error value in the same unit as the output variable.

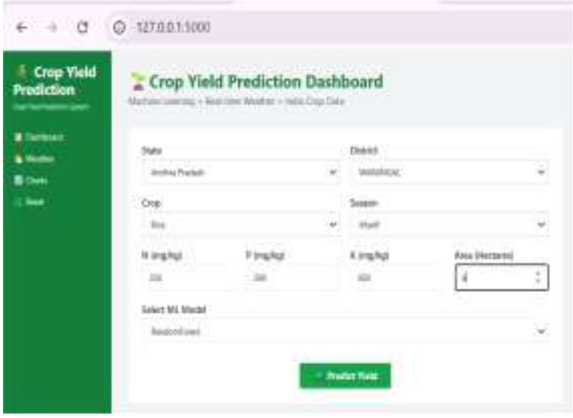
$$\text{RMSE} = \sqrt{[(\frac{1}{n})\sum (X - Y)^2]}$$

R-squared (R² Score or Coefficient of Determination)

R² represents the proportion of the variance in the dependent variable that is predictable from the independent variables.

$$R^2 = 1 - [\frac{\sum (X - Y)^2}{(X - \bar{X})^2}]$$

Where X¯ is the mean of the actual values.



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Crop Yield Prediction

Crop Yield Prediction Dashboard

State: Andhra Pradesh

District: WARANGAL

Crop: Rice

Season: Kharif

N (mg/kg)

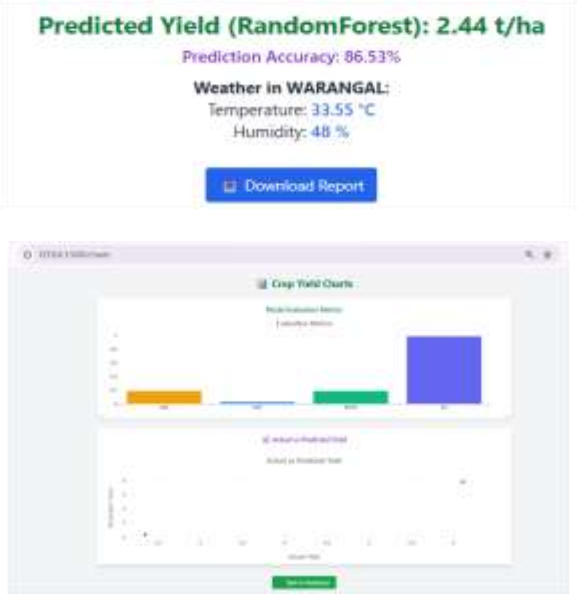
P (mg/kg)

K (mg/kg)

Area (Hectares): 4

Select ML Model: RandomForest

Fig 2: User input for parameters Crop, Season, N, P, K, Area (Random Forest)



Predicted Yield (RandomForest): 2.44 t/ha

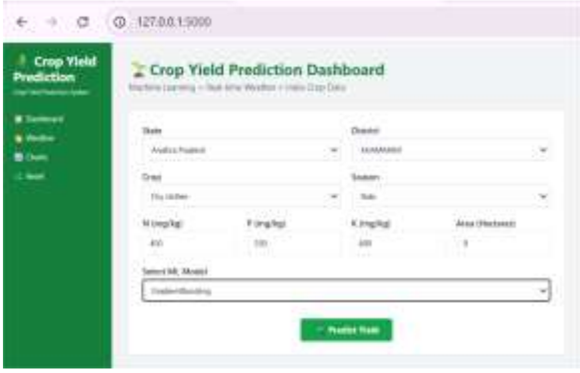
Prediction Accuracy: 86.53%

Weather in WARANGAL:

Temperature: 33.55 °C

Humidity: 48 %

Fig 3 :Predict result for given input parameters MAE,MSE,RMSE,R^2 (Random Forest)



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Crop Yield Prediction

Crop Yield Prediction Dashboard

State: Andhra Pradesh

District: WARANGAL

Crop

Season

N (mg/kg)

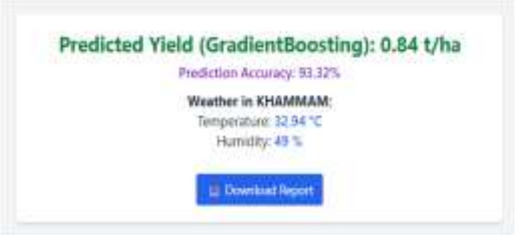
P (mg/kg)

K (mg/kg)

Area (Hectares)

Select ML Model: GradientBoosting

Fig 4: User input for parameters Crop, Season, N, P, K, Area (Gradient Boosting)



Predicted Yield (GradientBoosting): 0.84 t/ha

Prediction Accuracy: 93.32%

Weather in KHAMMAM:
Temperature: 32.94 °C
Humidity: 49 %

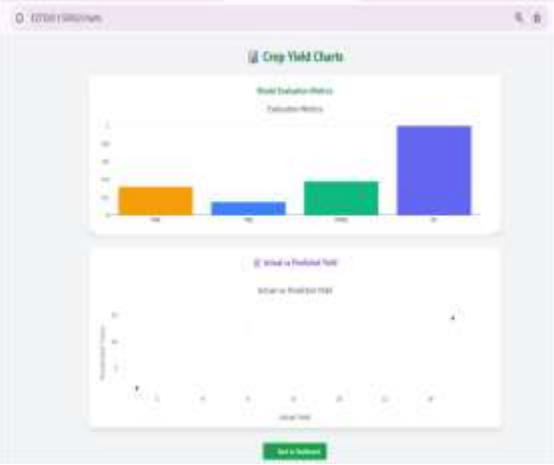
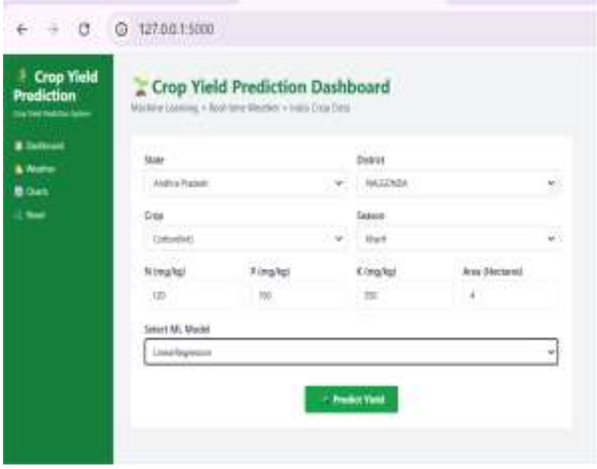


Fig 5: Predict result for given input parameters MAE, MSE, RMSE, R^2 (Gradient Boosting)



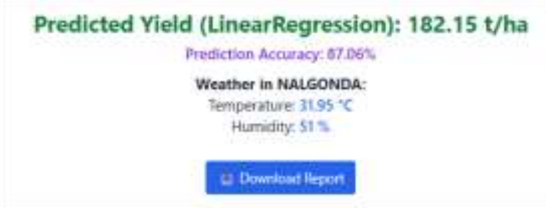
Crop Yield Prediction

Crop Yield Prediction Dashboard

Machine Learning + Real-time Weather + India Crop Data

State: Andhra Pradesh
District: NALGONDA
Crop: Cotton(lint)
Season: Kharif
N (mg/kg): 120
P (mg/kg): 100
K (mg/kg): 250
Area (Hectares): 4
Select ML Model: LinearRegression

Fig 6: User input for parameters Crop, Season, N, P, K, Area (Linear Regression)



Predicted Yield (LinearRegression): 182.15 t/ha

Prediction Accuracy: 87.06%

Weather in NALGONDA:
Temperature: 31.95 °C
Humidity: 51 %

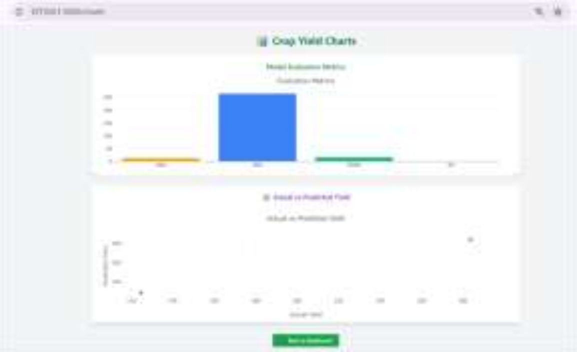


Fig 7: Predict result for given input parameters MAE, MSE, RMSE, R^2 (Linear Regression)

V. RESULTS AND DISCUSSION

The Random Forest model demonstrated the lowest MAE (2.34) and highest R² (0.91), followed by Gradient Boosting with similar performance. Linear Regression yielded lower accuracy due to its inability to handle non-linear interactions between soil nutrients and weather parameters. The dashboard provided immediate visual feedback on prediction quality, updating graphs dynamically after each user input. This functionality enhances user engagement and model interpretability. Integration with live weather APIs ensured realistic predictions influenced by daily climate conditions. The web interface achieved excellent responsiveness and scalability for deployment on Raspberry Pi or cloud environments.

5. CONCLUSION

This paper presented a Smart Indian Crop Yield Prediction System that leverages ML algorithms and live weather integration to improve agricultural decision-making. The system achieves practical performance and usability through a Flask-based web dashboard and automated metric computation.

6. FUTURE SCOPE

In the future, the system can be extended with:

- IoT-based soil sensors for live NPK updates
- Satellite NDVI and rainfall datasets for better spatial resolution
- Deep learning models (CNN, LSTM) for temporal crop prediction

- Cloud or mobile app deployment for farmers in remote areas
- Integration with government e-agriculture databases for automation

Such advancements will transform this prototype into a fully scalable precision-agriculture platform.

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