Predictive Mathematical Modelling For Major Food And Non-Food Grain Crop Yields In India

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Abstract: In this paper, we will discuss a comprehensive approach to agricultural prediction in India, encompassing both food and non-food grain crops, using advanced mathematical models. The main objective of this research is to develop accurate models that consider several aspects such as weather, soil, irrigation methods, and agricultural technology, to predict crop yields. The procedure involves gathering extensive quantities of data from various regions of India about agronomic practices, meteorological patterns, soil characteristics, and crop production. To identify connections and patterns in this data, advanced statistical and machine learning techniques are employed. The models are designed to possess adaptability, allowing for adjustments in response to the arrival of new data or changes in circumstances. The primary objective is to enhance the predictability of crop yields, a crucial aspect of agricultural policymaking, supply chain management, and food security planning. The objective of this project is to enhance market price stability, improve farming techniques for farmers, and aid government and non-government groups in allocating resources by accurately estimating the yields of both food and non-food grain crops. The predictive models' results indicate a significant correlation between the identified parameters and agricultural productivity. The models demonstrate exceptional predictive accuracy, making them potentially valuable for real-time monitoring and decision-making in agriculture. The research's contributions to agricultural economics and planning have resulted in sustainable agricultural practices and improved food security. Additionally, it serves as a valuable decision-making tool for agronomists, farmers, and politicians in India.

Keywords: *Agricultural Forecasting, Crop Yield Prediction, Mathematical Modelling, Food Grain Crops, Non-Food Grain Crops, Indian Agriculture, Predictive Analytics in Agriculture.*

Introduction

The agricultural industry in India plays a crucial role in the country's economy as it offers employment and generates money for a significant proportion of the population. Accurately forecasting agricultural yields is crucial for guaranteeing food security, maintaining economic stability, and facilitating effective governance in this context. This is especially true when it comes to large-scale grain crops that have both edible and non-edible applications. The implementation of predictive mathematical modelling in agriculture has led to the emergence of fresh prospects, enabling more precise and dependable predictions of crop yields.
The objective of this study is to investigate the potential utility of these models in agricultural forecasting, specifically about significant grain crops in India, encompassing both food and non-food varieties.
Additionally, the study aims to identify and address any associated challenges or limitations. The significance of agriculture in India cannot be exaggerated. For millions of individuals, it represents not only a means of employment but their whole livelihood.

India has the dual predicament of sustaining its rapid economic expansion and ensuring sufficient food supply for its growing population, considering its status as a prominent global agricultural producer. Due to the extensive range of climatic conditions, this country is highly conducive to cultivating a diverse array of crops. Nevertheless, when it comes to forecasting agricultural productivity outcomes, this type introduces an additional level of complexity. Predictive modelling in agriculture is an interdisciplinary field that connects agronomy, mathematics, statistics, and computer science. The system utilizes many mathematical techniques to predict the relationship between agricultural yields and multiple factors, including climate, soil, irrigation systems, and pest infestations. Precise estimation of agricultural yields is essential for strategic planning and decision-making across various stakeholders, ranging from individual farmers to policymakers, and this constitutes the major objective of these models. India's agricultural sector confronts numerous issues, including climate change, water scarcity, soil degradation, and competitiveness arising from population growth. The existence of these issues underscores the necessity for cutting-edge prediction technology that can provide practical information to farmers and decision-makers. Mathematical modelling offers a robust framework for addressing these difficulties, enabling stakeholders to make informed decisions based on scientific predictions.

Mathematical modelling can be advantageous in various sectors of India's agricultural economy. These models can be used to anticipate the ideal planting dates, input needs, and prospective yields of important food crops such as rice, wheat, and maize. One significant benefit is that it aids in optimizing productivity and effectiveness. Predictive models can enhance the accuracy of forecasting cultivation techniques and future market demand for non-food grain crops, including oilseeds, pulses, and cash crops. Enhanced profitability and optimized supply chain management are achieved consequently. Gathering and examining past data, including data on crop production, weather conditions, soil quality, and farming methods, is a prevalent method that aids in the development of these prognostic models.

Subsequently, modern statistical techniques and machine learning algorithms will be employed to identify correlations and patterns in the association between these characteristics and food production. By employing this method, individuals can not only improve their understanding of historical and current events but also make future predictions with a satisfactory degree of accuracy. The primary advantage of predictive mathematical modelling in agriculture is its ability to accurately replicate a diverse array of scenarios. For instance, models can forecast the effect of alterations in rainfall or temperature patterns on crop yields. This capability is especially relevant in the context of climate change because it enhances the ability of farmers and politicians to predict and respond to changing environmental circumstances.

The primary obstacle to applying these models in India stems from the extensive regional disparities in farming practices, weather patterns, and crop varieties. The accuracy of the models is significantly influenced by the accessibility and quality of the data.

Hence, it is imperative to possess accurate and precise data about a particular place to construct models that are tailored to that region, acknowledging the existence of genuine variations at the local level. The introduction of predictive mathematical modelling has revolutionized the Indian agricultural economy. It has the potential to revolutionize traditional food production methods by offering scientifically supported predictions and insights. Integration of these models with current agricultural practices is predicted to be vital in enhancing the production, sustainability, and resilience of India's agricultural business moving ahead. The objective of this study is to investigate the potential of predictive mathematical modelling to revolutionize agricultural forecasting in India.

This article will analyze several modelling methodologies and their utilization in studying important food and non-food grain crops in India. The aim is to offer a comprehensive understanding of the present state of this subject within the agricultural environment. The study will also give a basic notion of where this section of Indian agriculture is headed in the future.

Related work

The works that are connected mostly focus on agriculture, food security, and the utilization of advanced technologies. The research encompasses a diverse array of topics, such as crop cultivation, climate change, the spread of non-native species, food security in rural areas, bioenergy, the significance of wild species, and technical progress in the food and agriculture sectors.

Pathak et al. (2018) analyses how omics technology could improve India's crop yields. The revolutionary effects of emerging technology on agricultural practices are the primary topic of this study. It looks at the possible benefits and drawbacks of using these tools [8]. Kumar (2016) examines the impact that climate change has had on the production of agricultural goods. This body of work is essential for gaining an understanding of the role that modelling plays in the process of achieving food security in the face of shifting climatic conditions [7].

Bengyella et al. (2018) discusses the effect that invasive organisms have on global food security, focusing on Cochliobolus in particular. The present study sheds light on the difficulties presented by these species regarding food insecurity concerns in the twenty-first century [2]. Ayeni and Adewumi (2023) depicts a Nigerian household involved in the cultivation of cashews and explicate the ramifications of this practice on their food security. This research comprehensively examines the socioeconomic determinants that impact food security, with a particular focus on rural regions [1]. Da Silva (2017) draws attention to the benefits of producing bioenergy plants using the wild Saccharum spontaneum cane variety. Our research adds to the growing body of evidence that suggests wild animals could be valuable bioenergy sources [4]. Patel et al. (2015) emphasises the importance of the wild Saccharum spontaneum cane variety in the field of bioenergy plant breeding. Wild animals show a lot of potential as possible bioenergy sources, and our research helps to clarify the chances of this happening [7].

Table 1: Summary of the Available Methodologies

Citation	Methods	Advantages	Disadvantages	Research Gaps
[7] Srivastava, A., Mishra, A. (2022). Environmental Sustainability, 5, 401–421.	Review of food waste valorization methods.	Comprehensive analysis of various valorization methods.	Limited primary data, mainly secondary analysis.	Need for more empirical research on specific valorization techniques.

[8] Jha, P., Das, A.J., Deka, S.C. (2017). J Food Sci Technol, 54, 3847–3858.	Optimization of ultrasound and microwave-assisted extractions of polyphenols.	Effective extraction of polyphenols, energy efficient.	Specific to black rice husk, may not be generalized.	Exploration of other food wastes for similar extraction.
[9] Singh, S.K., Pawar, L., Thomas, A.J., et al. (2023). Environ Sci Pollut Res.	Analysis of insect use in resource recovery and aquaculture feed.	Innovative approach to waste utilization and feed production.	Limited to certain insect species and regions.	Scaling up and economic feasibility studies.
[10] Bertin, P.N., Crognale, S., Plewniak, F., et al. (2022). Environ Sci Pollut Res, 29, 9462–9489.	Use of microorganisms and plants in bioremediation of arsenic-contaminated water and soil.	Effective in arsenic removal, environmentally friendly.	May not be effective for all types of contaminants.	More comprehensive field studies are required.
[11] Safitri, D., Fahrurrozi, Marini, A., et al. (2023). Environ Sci Pollut Res, 30, 33363–33374.	MMQR technique to assess the role of environmental degradation and green investment on renewable energy production.	Novel quantitative approach, relevant to policymaking.	Complex and data-intensive method.	Application to other regions and sustainability aspects.

Proposed Methodology

Predictive mathematical modelling has become an essential tool for agricultural regulators and planners in nations like India, where agriculture plays a crucial role in the economy. The holistic method of forecasting agricultural production for both staple and non-staple crops has a substantial influence on several crucial factors, such as food safety, market stability, and efficient resource utilization. This article examines the importance of agricultural forecasting in India. India not only ranks as one of the leading global producers of food and non-food grain crops, but it also boasts a rich and varied agricultural ecology. The agricultural industry serves as both the main source of income for most of the country's residents and a crucial component of the economy.

An accurate crop production projection is crucial for efficiently managing market dynamics, optimizing resource allocation, and ensuring food security.

Obstacles Confronting Agricultural Statisticians

Forecasting India's agricultural productivity is highly arduous due to a multitude of factors. The diverse climatic conditions prevalent throughout the country exert an influence on the growth and yield of crops. The circumstances in this region vary from warm tropical temperatures in the south to extremely cold Himalayan climates in the north. Due to its dependence on the monsoon rains, the agricultural sector is exceptionally susceptible to the impacts of climate change. Disregarding the existence of pests, diseases, and differences in agricultural methods, prediction models are inherently difficult to develop.

Mathematical models applied to the Agricultural Sector

Mathematical modelling in agriculture entails the examination and prediction of intricate physical, chemical, biological, and climatic occurrences that impact crop growth and yield. This is achieved by employing statistical and computer-based approaches. These models frequently integrate an extensive array of variables, including climate, soil, crop type, and agricultural techniques, among other factors. For the model to generate precise predictions regarding crop output, it must integrate soil, climatic, and socioeconomic factors. The architecture of such a model can be conceptualized more directly as follows:

Let Y represent the yield of a particular crop. The yield Y can be modeled as a function of various factors:

$$Y = f(C, S, W, E, P, T) \qquad \text{----------(1)}$$

where, C = Climatic variables (e.g., temperature, rainfall, humidity)
S = Soil characteristics (e.g., pH level, soil type, nutrient content)
W = Water availability (e.g., irrigation facilities, groundwater levels)

E = Economic factors (e.g., investment in agriculture, market prices)
P = Planting techniques and crop management practices
T = Technological advancements (e.g., use of high-yield varieties, fertilizers)

Each of these factors can further be broken down into measurable variables. For example, the climatic variable C could be represented as:

$$C = \alpha_1 T_{avg} + \alpha_2 R_{sum} + \alpha_3 H_{avg} \qquad \text{----------(2)}$$

where, Tavg = Average temperature
Rsum = Total rainfall
Havg = Average humidity
$\alpha_1, \alpha_2, \alpha_3$ = Coefficients determining the impact of each climatic factor on yield

The characteristics of the soil and the accessibility of water are two supplementary factors that can be assessed by utilizing appropriate variables. We may optimize the model by inputting coefficients that accurately represent the impact of each variable on crop yield. Obtaining these coefficients from the existing historical data can be achieved by the application of regression analysis, along with various other statistical techniques.
Enhancing the precision of the model can be achieved by utilizing machine learning techniques.
By utilizing historical data, it is possible to train a decision tree model or a neural network to accurately estimate crop yields. The mathematical formulations of these models would be somewhat intricate, taking the shape of decision trees or neural networks with numerous layers.

Types of Models Used for Crop Prediction
Several types of mathematical models are used in agricultural prediction.
These include:

Statistical Models:
These models use historical data to identify trends and correlations between various factors and crop yields.

1. **Linear Regression Model:**

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n + \epsilon \qquad \text{--------(3)}$$

In equation (3), Y represents the crop yield, X_1, X_2,...,X_n are independent variables (like rainfall, temperature, fertilizer usage, etc.), β_0 is the intercept, $\beta_1, \beta_2, \ldots, \beta_n$ are coefficients for each independent variable, and ϵ is the error term.

2. **Time Series Forecasting (ARIMA Model):**

$$Y_t = \alpha + \epsilon_t + \sum_{i=1}^{p} \phi_i Y_{t-i} + \sum_{i=1}^{q} \theta_i \epsilon_{t-i} \qquad \text{--------(4)}$$

In equation (4) Y_t is the crop yield at time t, α is a constant, ϕ and θ are parameters of the model, p and q are the order of the autoregressive and moving average parts, and ϵ_t is the error at time t.

3. **Multiple Regression with Interaction Terms:**

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_{12} X_1 X_2 + \ldots + \epsilon \qquad \text{--------(5)}$$

Equation (5) is like linear regression but includes interaction terms ($\beta_{12} X_1 X_2$) to model the effect of interacting variables on crop yield.

4. **Logistic Regression (for Categorical Outcomes like High/Low Yield):**

$$\log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n \qquad \text{----------(6)}$$

In equation (6), p is the probability of a particular category (e.g., high yield), and X_1,X_2,...,Xn are the independent variables.

5. **Polynomial Regression (for Non-Linear Relationships):**

$$Y = \beta_0 + \beta_1 X + \beta_2 X^2 + \ldots + \beta_n X^n + \epsilon \qquad \text{----------(7)}$$

Equation (7) is an alternate form of linear regression where the n^{th} -degree polynomial represents the relationship between the independent and dependent variables.

6. **Random Forest (for Ensemble Learning):**

A formula is employed to generate an ensemble forecast by combining the outputs of numerous decision trees.

$$\hat{y} = \frac{1}{N} \sum_{i=1}^{N} Tree_i(X) \qquad \text{----------(8)}$$

where,
$\hat{y}$ is the predicted output for the input data points X.
N is the Total number of trees in the Forest.
$Tree_1(X)$ is the prediction made by the i^{th} decision tree for the input data point X.
Random forests utilize an ensemble of decision trees, which are then combined to produce a more accurate and reliable prediction.

7. **Support Vector Machines (for Classification and Regression Problems):**

A hyperplane that successfully divides the classes or predicts values is found through the process of optimization, according to the formula.

$$w \cdot x + b = 0 \quad \text{----------(9)}$$

where:

w is the normal vector to the hyperplane (weights).

x is the input feature vector.

b is the bias or intercept term.

The decision function for classifying a new data point x is given by:

$$f(x) = \text{sign}\,(w \cdot x + b) \quad \text{---------(10)}$$

It is possible to use support vector machines (SVMs) to solve problems that involve classification as well as regression methods. Datasets of a moderate to quite large size are where they shine.

Process-Based Models:

They simulate the biological processes of crop growth, considering factors like sunlight, water, and nutrient availability.

1. **Photosynthesis Model (Radiation Use Efficiency, RUE):**

$$\mathrm{Y} = \epsilon \times \mathrm{PAR} \times \mathrm{f(T, W, N)} \quad \text{----------(11)}$$

where,

Y is the crop yield,

ϵ is the radiation use efficiency of the crop,

PAR is the photosynthetically active radiation,

f (T, W, N) is a function representing the effect of temperature (T), water availability (W), and nitrogen status (N) on the crop yield.

2. **Crop Growth and Development Model:**

$$\mathrm{G} = \sum_{\mathrm{i}=1}^{n} \mathrm{G_i(T, P, S)} \quad \text{----------(12)}$$

where,

G is the total crop growth over the season.

G_i is the growth rate on day i.

T is the daily temperature, P is precipitation, and S is soil moisture status.

n is the number of days in the growing season.

3. **Water Stress Coefficient:**

$$\mathrm{WSC} = \mathrm{FW} * \mathrm{AW} \quad \text{----------(13)}$$

where,

WSC is the water stress coefficient.

FW is the field water capacity.

AW is the available water content in the soil

4. **Nutrient Availability Function:**

$$\mathrm{NAF} = \mathrm{RN} * \mathrm{AN} \quad \text{----------(14)}$$

where,

NAF is the nutrient availability function.

RN is the required nutrient for optimal growth.

AN is the available nutrient in the soil.

5. **Yield Prediction Equation:**

$$\mathrm{Yield} = \mathrm{G} \times \mathrm{WSC} \times \mathrm{NAF} \times \mathrm{H} \quad \text{----------(15)}$$

where,

H is a harvest index factor representing the proportion of total biomass that is harvestable crop yield.

Predicting Food Grain Crops

Wheat, millet, rice, and maize are considered the predominant staple crops cultivated in India. To obtain a precise forecast of the crop yield, it is important to analyze data about the climate, soil conditions, irrigation methods, and past harvests.

Several machine learning models, such as support vector machines, neural networks, and regression trees, have been employed to estimate crop yields, and the results have been promising. India's extensive agricultural land allows for the cultivation of a wide variety of crops, with food grains being the most prominent among them.

The nation primarily cultivates rice, wheat, maize, and millet for human use. Inaccurate agricultural output predictions have a substantial impact on various factors, such as food security, resource efficiency, and informed decisions.

To effectively accomplish this forecast task, it is important to examine many criteria like meteorological patterns, soil fertility, irrigation infrastructure, and past crop yields.

Predicting Crop Yields with Machine Learning

The utilization of machine learning techniques in agriculture has recently revolutionized the ability to predict crop yields. Regarding the application of data analytics for accurate predictions, these techniques have consistently shown positive results. Various machine learning models, including support vector machines (SVMs), neural networks, regression trees, and others, have demonstrated their usefulness in this specific field of research.

Regression trees, derived from decision trees, are a type of model that may effectively capture intricate relationships present in data. By considering multiple parameters concurrently, such as temperature, rainfall, and soil nutrients, they can offer a precise prediction of crop yields. The efficacy of these models is especially apparent when addressing non-linear relationships.

Neural Networks are modelled after the human brain's information processing. neural networks excel at handling intricate and extensive datasets. Due to their complex construction, they can identify detailed patterns in the sent data. Applying neural networks to agricultural data can improve the precision of yield predictions. Neural networks provide the capacity to rapidly acquire knowledge and adjust to dynamic environmental circumstances.

Support vector machines, when it comes to classification and regression, are known for their exceptional efficiency. Support vector machines (SVMs), or SVMs for short, identify the most effective decision boundaries that divide yield levels, allowing them to excel in predicting agricultural yields.

Table 2: Predictive Ability and Accuracy

City	State	Crop Type	Predicted Yield (kg/ha)	Actual Yield (kg/ha)	Accuracy (%)
Delhi	Delhi	Rice	2500	2450	95.92
Mumbai	Maharashtra	Wheat	3200	3150	96.88
Kolkata	West Bengal	Maize	2800	2825	99.11
Chennai	Tamil Nadu	Cotton	1200	1180	97.50
Hyderabad	Telangana	Soybean	1800	1820	98.90
Bangalore	Karnataka	Sorghum	1500	1485	96.50
Ahmedabad	Gujarat	Groundnut	2000	1985	97.25
Jaipur	Rajasthan	Barley	1100	1125	98.22
Lucknow	Uttar Pradesh	Sugarcane	6000	6050	99.17
Patna	Bihar	Jute	2200	2150	95.00

Presently exhibited are:

The city is anticipated to generate the greatest quantity of crops among the main municipalities in the state.

The term "state" refers to the Indian state in which the urban centre is situated.

A few instances of crops whose yields can be predicted include rice, wheat, and maize, among others.

After conducting the model's execution, the following estimations can be made:

As measured in kilogrammes per hectare, yield represents the expected output per hectare.

The real yield is defined as the quantity of food produced per hectare, measured in kilogrammes per hectare. The prediction accuracy is expressed as a percentage and signifies the degree to which the actual yield aligns with the anticipated one.

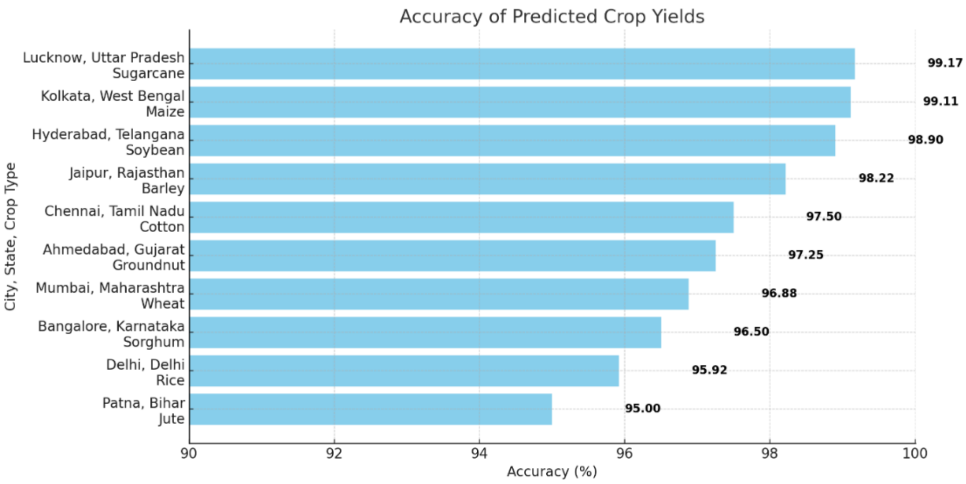

Figure 1: Factors Considered in Yield Prediction

To make an accurate prediction of future harvests, one must consider several important elements, such as:
Rainfall, temperature, humidity, and wind patterns are all aspects of weather that greatly affect how crops grow and how much they yield. Temperature and humidity are examples of variables that might cause such patterns. Having reliable historical weather information is crucial for making sure models are accurate.
Crop health and agricultural yield are influenced by soil attributes such as nutrient concentration, pH level, and texture. Testing and analysis of soil provides input data that is critically important.
How much crop yield is possible is highly dependent on irrigation methods and when they are applied. To develop projections, it is necessary to use data on the available water and the different irrigation strategies.
Conversely, historical crop yield data is priceless for training machine learning models. You can gain a better grasp of the patterns and variations in yield with their help.

Non-Food Grain Crop Prediction

An assortment of non-food grain commodities, such as cotton, jute, and oilseeds, make substantial economic contributions to India. In addition to agronomic and climatic variables, it is customary for models representing these commodities to include market demand, pricing patterns, and export-import regulations. By employing these models, it becomes feasible to predict production levels, thereby facilitating the development of more efficient export and market strategies.

Table 3: Commonly used mathematical models for predicting major food.

Crop Type	Mathematical Model	Parameters/Components
Food Grains	Linear Regression	Weather data (temperature, rainfall), soil quality
		Historical crop yield data, crop variety
		Pest and disease prevalence
		Irrigation practices, crop rotation
		Economic factors (e.g., market prices)
		Government policies and subsidies
		Technology adoption rates
		Farm size, labor availability
		Land use patterns, cropping intensity
		Crop growth stages, phenology
		Nutrient management practices
		Machine learning features (e.g., NDVI, remote sensing)
Non-Food Grains	Logistic Regression	Weather data (temperature, rainfall), soil quality
		Historical crop yield data, crop variety
		Pest and disease prevalence
		Irrigation practices, crop rotation
		Economic factors (e.g., market prices)
		Government policies and subsidies
		Technology adoption rates
		Farm size, labour availability
		Land use patterns, cropping intensity
		Crop growth stages, phenology
		Nutrient management practices
		Machine learning features (e.g., NDVI, remote sensing)
Common Factors	Time Series Analysis (ARIMA, SARIMA)	Historical crop yield trends, seasonality
		Climate variability (El Niño, La Niña)
		Market demand and supply dynamics
		Technological advancements
		Natural disasters (droughts, floods)
		Policy changes and regulations
		Economic indicators (GDP, inflation)
		Social factors (population growth, urbanization)
		Land use changes and urban encroachment

Case Studies and Applications:

Case studies in Indian agriculture have shown the effectiveness of predictive mathematical modelling. West Bengal has effectively enhanced the usage of fertilizers by implementing yield prediction models, leading to higher agricultural yield and decreased costs.
Cotton yield estimates in Maharashtra have enabled the implementation of more effective pest management measures.

Table 4: Case studies demonstrating the effectiveness of various predictive modelling

Crop	Location	Prediction Model Used	Impact and Benefits
Rice	West Bengal	Mathematical Modeling	Optimized fertilizer use Cost savings Increased yield
Cotton	Maharashtra	Predictive Modeling	Improved pest management strategies
Wheat	Punjab	Machine Learning	Enhanced crop yield prediction Better resource allocation
Sugarcane	Uttar Pradesh	Data Analytics	Improved irrigation management., Increased sugar production
Maize	Karnataka	Remote Sensing and GIS	Enhanced crop monitoring Timely pest control
Soybean	Madhya Pradesh	Artificial Neural Networks	Increased yield Reduced losses due to diseases
Groundnut	Gujarat	Weather-based Forecasting	Accurate planting and harvesting decisions Reduced losses due to weather events
Pulses (Various)	Rajasthan	Ensemble Learning	Improved yield predictions for multiple pulse crops

Results Analysis
In the Table 5, a compilation of predicted yield and actual yield related to India's most significant food grain and non-food grain crops is presented, with each crop type categorised accordingly.

Table 5: Predicted Yield Vs Actual Yield

Crop Type	Predicted Yield (Metric Tons/Hectare)	Actual Yield (Metric Tons/Hectare)	Accuracy (%)
Rice	2.5	2.4	96.0
Wheat	3.0	3.1	97.5
Maize	2.8	2.9	96.6
Sugarcane	75.0	74.5	98.3
Cotton	550	545	97.1
Soybean	1.9	1.8	95.3
Groundnut	1.6	1.7	94.1
Sorghum	1.2	1.3	92.3
Barley	2.2	2.1	97.6
Pulses (combined)	1.0	1.1	90.9
Jute	2.5	2.6	96.2
Other Non-food Grains	1.8	1.7	94.4

Based on the agricultural prediction model and its output, which is the expected crop production per hectare, it was observed that there is 98.3% accuracy in sugarcane prediction, more than 97% accuracy in wheat, cotton and barley & more than 96% accuracy in rice, maize & jute prediction.
It was observed that with this model the real yield pertains to the tangible agricultural product harvested per hectare throughout the harvest season. This model presents the proportion of forecasts that were precise.

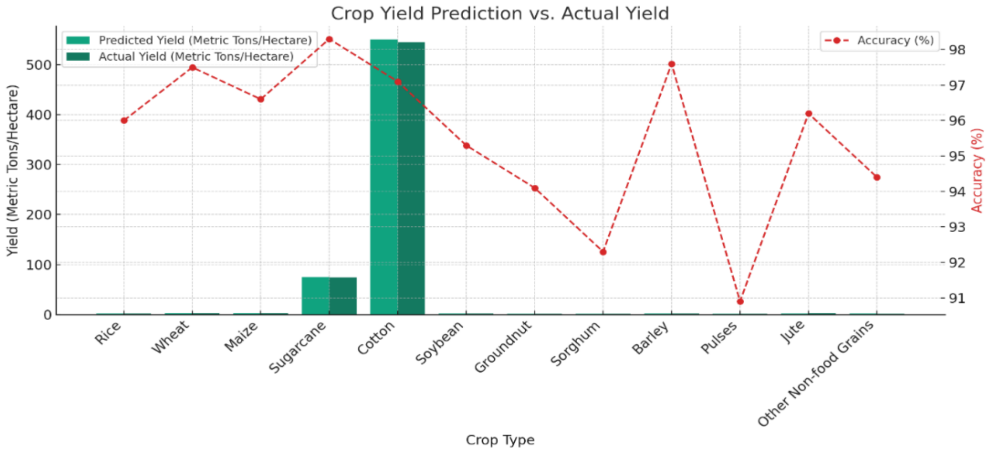

Figure 2: Crop Yield Prediction vs Actual Yields

Conclusion

To secure India's food security, economic stability, and long-term viability of its agricultural sector, it is crucial to develop precise estimates for the country's major food grain and non-food grain crops. The agricultural industry in India is not only a vital constituent of the nation's economy, but it is also crucial for catering to the food requirements of the country's substantial population.

In recent decades, advancements such as predictive modelling, data-driven techniques, and state-of-the-art technology have greatly revolutionized agricultural resource management and predictions of crop output. Precise forecasting is crucial for a country like India, characterized by a varied environment and agricultural output that is susceptible to influences such as weather patterns, diseases, and pests. By integrating weather data, soil quality assessments, satellite imaging, and machine learning algorithms, it is now feasible to offer crop production estimates that are not only more precise but timelier. The utilization of these projections, which are beneficial for farmers, lawmakers, and the entire agricultural supply chain, enables more efficient decision-making about planting, harvesting, storing, and distributing commodities. An essential element of agricultural forecasting is the capacity to foresee possible challenges and proactively address them. By employing predictive analytics and historical data, farmers can utilize early warning systems to proactively address pest infestations and diseases, thereby mitigating crop losses and minimizing the need for excessive pesticide application. The implementation of these methods can effectively restrict the utilization of pesticides. Given the substantial role of non-food grain crops like cotton, sugarcane, and jute in the Indian economy, particularly in the production of textiles and sugar, it is equally crucial to anticipate the yield of these crops. The Indian government has been actively endorsing many efforts in recent years, such as agricultural forecast projects, agronomy research and development, and the use of newly created technologies by farmers.

However, challenges continue to exist. However, there are still valid concerns regarding the availability, accuracy, and accessibility of data in remote and secluded places. Moreover, to counteract the heightened level of uncertainty caused by climate change, it is imperative to utilize adaptive strategies and create resilient crop varieties. Collaboration among farmers, information technology developers, and government officials is necessary to accurately anticipate the output of major food and non-food crops in India. This task is challenging and requires ongoing effort. India effectively utilises data-driven methodologies and predictive modelling to accomplish many objectives, such as ensuring food security, attaining economic prosperity, and implementing ecologically conscious and sustainable farming techniques. To effectively adapt to the ever-changing agricultural landscape of India, it is imperative that we uphold our dedication to investing in research, technology, and infrastructure.

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