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Smart Farming System for Price Prediction and Resource Optimization Using Machine Learning

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Abstract - India's agriculture faces challenges like fluctuating crop prices, unpredictable weather, and limited resources, affecting farmers' productivity and income. To address this, our smart farming system uses machine learning algorithms like Decision Tree, Random Forest, and K-Nearest Neighbors to predict crop prices and optimize resource usage. It also offers weather predictions, crop recommendations, and fertilizer suggestions to help farmers plan activities effectively. Interactive land maps assist in identifying optimal farming locations, enhancing resource management. Additionally, a chatbot provides real-time advice on crop selection, pest control, and market trends. This system empowers farmers with data-driven insights, boosting productivity and economic growth.

***Key Words*:** Ensembled Learning, Crop price prediction, Resource Optimization, Fertilizer Recommendation.

1. INTRODUCTION

India's agriculture faces challenges like fluctuating crop prices, unpredictable weather, and limited access to modern resources, affecting farmers' productivity and profitability. To address this, a smart farming system powered by machine learning is developed to predict crop prices, optimize resource usage, and support decision-making. Algorithms like Decision Tree, Random Forest, and K-Nearest Neighbors analyze factors such as rainfall, location, and market trends for accurate price forecasts, helping farmers reduce risks and maximize profits. The system also offers weather predictions, crop recommendations, and fertilizer suggestions, aiding in better crop management. Interactive maps help identify optimal farming locations based on water availability and soil conditions. Additionally, a chatbot provides real-time assistance on crop selection, pest control, and market trends. Machine learning further enhances agriculture by automating tasks, detecting pests early, and monitoring livestock health. These data-driven insights empower farmers to improve productivity and sustainability. This project aims to revolutionize agriculture, ensuring better profitability for farmers and contributing to India's economic growth.

2. LITERATURE REVIEW

[1] S. Yoon, T.H. Kim, D. Sub Kim, "Data-driven analysis of climate impact on tomato and apple prices using machine learning" on Science Direct Year: 2025 Volume: 11 Issue: pages: 56-67.
This research explores the impact of climate change on tomato and apple prices using machine learning to analyze historical climate data (e.g., temperature, rainfall) and market trends. It highlights how extreme weather events and gradual climate shifts significantly affect production yields, quality, and price fluctuations. By integrating climate models with market analysis, the study offers predictive insights to help farmers and policymakers anticipate price volatility, adapt to climate risks, and enhance agricultural resilience, ultimately aiming to minimize economic losses and ensure sustainable farming.

[2] F. Sun, X. Meng, Y. Zhang, Y. Wang, H. Jiang, P. Liu "Agricultural product price forecasting methods: A review" on IEEE Year:2023, Volume:13, Issue: 9 Pages: 96- 116.
This paper reviews methodologies for forecasting agricultural prices, highlighting their importance for stakeholders in decision-making and risk management. It categorizes approaches into traditional methods like time series analysis, valued for simplicity but limited in capturing complex patterns, and advanced machine learning techniques like neural networks, capable of modeling intricate data relationships. The study emphasizes integrating external factors such as weather, market trends, and policies to improve accuracy, while addressing challenges like data quality and availability. It offers insights into strengths and weaknesses of forecasting methods, 7 serving as a resource to advance agricultural price prediction.

[3] C. Shang, S. Bengio, B. Recht, O.Viyals "Understanding deep learning(still) requires rethinking generaliztion" published in IEEE Year: 2021 Volume: 64 Issue: 3 Page no.: 107-115.
This system addresses the challenge of understanding how deep learning models generalize to unseen data. Traditional frameworks, like the bias-variance tradeoff, fail to explain why highly overparameterized models often generalize effectively. The paper emphasizes factors such as implicit regularization through optimization techniques like stochastic gradient

descent and the impact of architecture choices and training complexity. Despite empirical successes, a comprehensive theoretical foundation is lacking. The authors advocate for further research to enhance the understanding and robustness of deep learning models in generalizing new data.

[4] L.Fang, P.C. Struik, C. Girousse, X.Yin, P. Martre,"Source-sink relationships during grain filling in wheat in response to various temperature, water deficit, and nitrogen deficit regimes", on Field Crops Research Year : 2024 Vol no: 75 Issue: 20 Pages: 6563-6578.
This study examines how environmental stress factors—such as high temperature, water deficit, and nitrogen deficiency—impact wheat growth during the grain-filling stage, a crucial phase for yield and quality. These stressors disrupt the source-sink relationship, which governs the flow of assimilates from photosynthetic organs to developing grains, reducing grain weight and yield. Combined stressors have a synergistic effect, exacerbating negative impacts on grain filling and protein content. The study emphasizes breeding wheat varieties resilient to such stresses and implementing integrated crop management strategies to optimize productivity amid climate variability.

3. EXISTING SYSTEM

The existing agricultural price prediction system relies solely on LSTM models, which, while effective for analyzing past price trends, fail to consider crucial external factors like climate conditions, economic policies, and supply chain disruptions. Its narrow focus on tomatoes and apples limits applicability to other crops with unique market dynamics. The system also lacks real-time data integration, preventing farmers from making timely decisions based on current market trends. Personalized recommendations are absent, ignoring factors like farm size, resources, and regional climate conditions that influence agricultural decisions. Relying on a single algorithm reduces adaptability to sudden market shifts, making predictions less reliable. Incorporating multiple algorithms or hybrid approaches could improve accuracy and robustness. Additionally, the system's lack of interactive features prevents farmers from providing real-time data and receiving personalized advice. Interactive elements would enhance engagement, allowing farmers to refine predictions and access tailored recommendations. To increase its utility, the system must integrate diverse crop data, real-time insights, and personalized guidance. A more comprehensive and adaptable approach will empower farmers with timely, accurate information for better decision-making.

4. PROPOSED SYSTEM

The proposed system is an advanced agricultural tool designed to assist farmers in making informed decisions regarding crop pricing and fertilizer recommendations. It integrates machine learning-based crop price prediction with a dynamic threshold mechanism and a fertilizer recommendation module, ensuring efficient agricultural planning and productivity.

At the core of the system is a machine learning model trained to predict crop prices per kilogram based on historical market trends and real-time data. This prediction model considers various factors, including seasonal fluctuations, demand-supply patterns, and geographical conditions. To enhance decision-making, the system implements a dynamic threshold for each crop, determining whether intervention is necessary. If the predicted minimum price of a crop falls below its specific threshold, the system triggers an automated recommendation process.

The fertilizer recommendation module is seamlessly integrated with the price prediction model. If a crop's predicted price is lower than its threshold, a 'Fertilizer' button appears, redirecting the user to a dedicated fertilizer recommendation page. This module utilizes a dataset mapping specific crops to optimal fertilizers, ensuring that farmers receive data-driven recommendations tailored to their needs. Additionally, the system considers factors such as soil health, weather conditions, and government agricultural schemes, providing a holistic approach to farming enhancement.

Advantages

- **Accurate Crop Price Prediction:** The system leverages machine learning algorithms to forecast crop prices, enabling farmers to make data-driven decisions about selling their produce at the right time.
- **Dynamic Threshold Mechanism**: Each crop has a predefined threshold value based on market trends, ensuring that price-based recommendations are relevant and effective.
- **Seamless Integration:** The price prediction module is directly linked with the fertilizer recommendation system, facilitating a smooth transition for farmers needing intervention.
- **Personalized Fertilizer Recommendations**: Based on the crop type and prevailing conditions, the system suggests the most suitable fertilizers, optimizing yield and reducing input costs.
- **Proactive Decision-Making:** By identifying low crop prices in advance, farmers can take preventive actions, such as adjusting fertilizer usage or exploring government subsidies.
- **Enhanced Agricultural Productivity:** The system promotes efficient resource utilization, contributing to increased crop yield and sustainable farming practices.

By offering a comprehensive and user-friendly solution, this system empowers farmers with the insights needed to maximize profitability and ensure long-term agricultural sustainability.

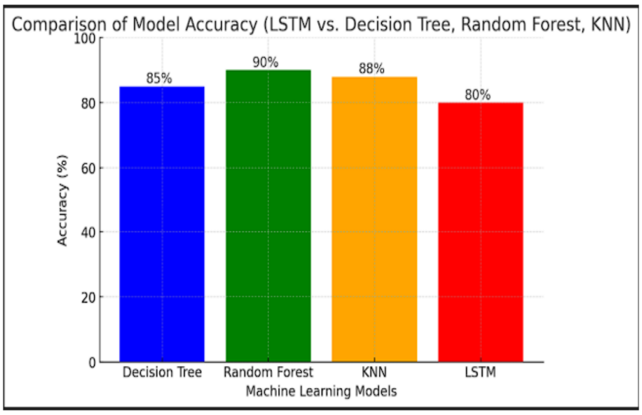


Figure 4.1 Comparison between LSTM vs Decision tree, Random Forest , KNN

5. SYSTEM OVERVIEW

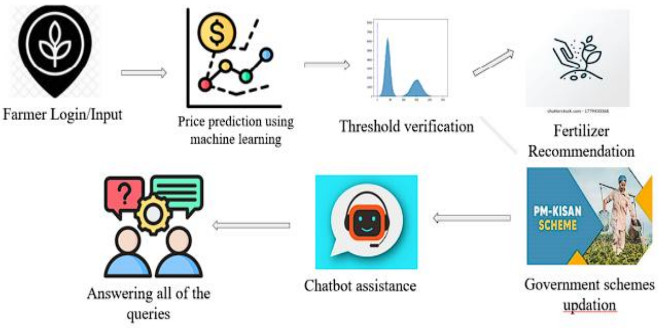


Figure-1 Architecture of the system

The Crop Price Prediction and Recommendation System empowers farmers with price forecasts, fertilizer suggestions, and access to government schemes. Farmers input crop details, and machine learning algorithms like Decision Tree, Random Forest, and KNN predict minimum and maximum prices. A threshold verification step checks if the predicted price is favorable, triggering fertilizer recommendations if needed. Admins update government schemes, while a Mistral AI-powered chatbot offers real-time assistance on crops, fertilizers, prices, and schemes. This integrated system enhances farmers' decision-making and profitability.

6. SYSTEM IMPLEMENTATION

6.1 Admin/Farmer Login

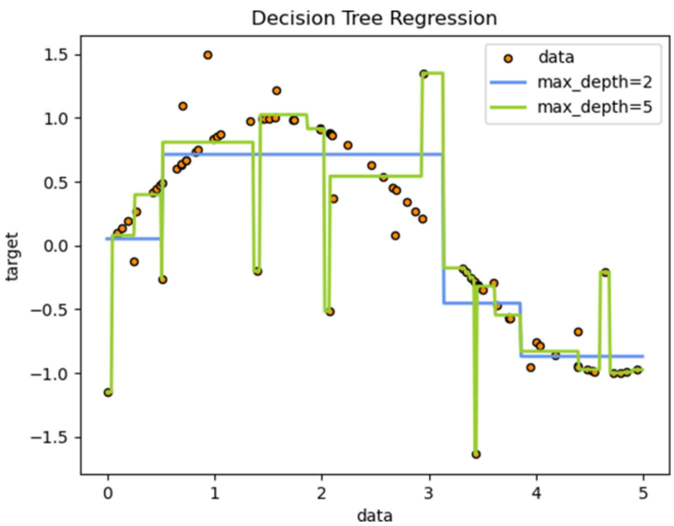
The Admin/Farmer Login Module ensures secure, role-based access, allowing farmers to access crop price predictions, fertilizer recommendations, and government schemes, while admins manage backend operations and update content. Built on Django's authentication system, it uses hashed passwords, session management, and role-based access control (RBAC) to safeguard data. Farmers get personalized dashboards to analyse market trends and interact with a chatbot for real-time support, while admins control platform content and ensure data accuracy. The module integrates seamlessly with crop prediction and fertilizer recommendation features, enhancing user experience. Overall, it offers robust security, personalized access, and smooth integration across the system.

6.2 Data Input and Price Prediction

The Crop Price Prediction Module helps farmers anticipate market trends by predicting crop prices based on factors like location, crop type, and market details. Built with Django, it uses Pandas for data handling, NumPy for numerical operations, and Scikit-learn for implementing machine learning models like Decision Tree, Random Forest, and K-Nearest Neighbors (KNN). LabelEncoder converts categorical data into numerical format, while train-test splitting ensures proper model validation. The models are evaluated using Mean Absolute Error (MAE) and R^2 Score for accuracy. This empowers farmers with insights for better planning and decision-making.

Mathematical/Algorithmic Foundations:

1. Decision Tree Regressor: A Decision Tree works by splitting the dataset into smaller subsets based on certain conditions. For regression tasks (like predicting crop prices), it tries to find the best way to split the data so that the difference between the actual and predicted prices is minimized.



Splitting Criterion:

The algorithm uses Mean Squared Error (MSE) or Mean Absolute Error (MAE) to decide

where to split:

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$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

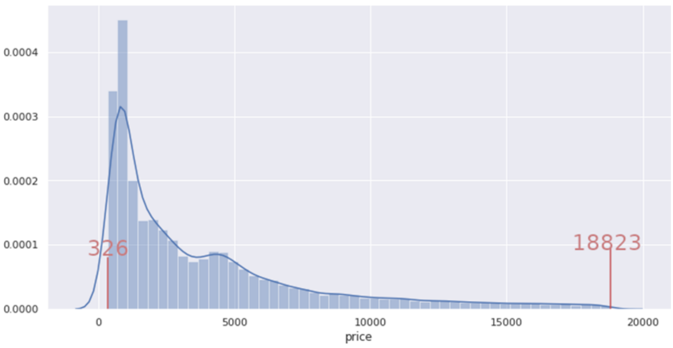
y_i = Actual crop price

$\hat{y}_i$ = Predicted crop price by the model

n = Number of samples

- ➢ The tree starts at the root and divides the data into two groups based on a condition (e.g., if the 'State' or 'Market' value is less than some threshold).
- ➢ It calculates MSE after each split.
- ➢ The split that results in the lowest MSE is chosen.
- ➢ This process repeats recursively, creating branches, until:
- ➢ Maximum depth is reached
- ➢ No further improvement in error

2. Random Forest Regressor: A Random Forest is an ensemble of multiple Decision Trees, each trained on random data samples (bootstrapping) and using random feature subsets at each split. The final prediction is the average of all trees' outputs, reducing overfitting and improving accuracy by creating more robust predictions.



Final Prediction Formula:

$$\hat{y}_{final} = \frac{1}{T}\sum_{t=1}^{T}\hat{y}_t$$

- T = Number of Decision Trees in the forest
- $\hat{y}_t$ = Prediction from each individual tree

3. K-Nearest Neighbors (KNN) Regressor :

KNN predicts crop prices by finding the k most similar historical records using Euclidean Distance and averaging their prices to make the prediction.

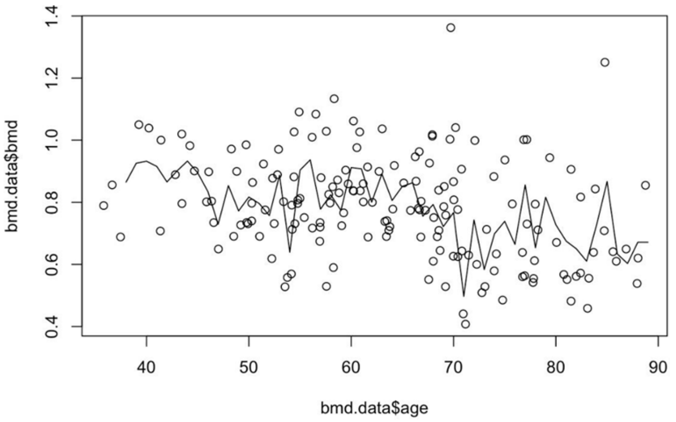


Fig KNN Regressor

Distance Calculation:

Most commonly, Euclidean Distance is used:

$$d = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}$$

- x_i = Feature values of the new data point (e.g., crop name, state, month)
- y_i = Feature values of a data point in the training set
- d = Distance between the new point and each point in the training set

Prediction Formula:

$$\hat{y} = \frac{1}{k}\sum_{i=1}^{k}y_i$$

- k = Number of nearest neighbors
- y_i = Actual prices of the k closest neighbors

4. Ensemble Prediction :

All three models (Decision Tree, Random Forest, KNN) and combine their predictions to get a final, more stable result.

$$\hat{y}_{ensemble} = \frac{\hat{y}_{DT} + \hat{y}_{RF} + \hat{y}_{KNN}}{3}$$

- $\hat{y}_{DT}$ = Prediction from Decision Tree
- $\hat{y}_{RF}$ = Prediction from Random Forest
- $\hat{y}_{KNN}$ = Prediction from KNN

Each model has its own strengths:

- ➢ Decision Trees handle non-linear patterns well.
- ➢ Random Forest reduces variance and avoids overfitting.
- ➢ KNN is simple and based on actual historical data.

By averaging their results, you smooth out errors and get more reliable predictions.

Evaluation Metrics Integration:

1.Mean Absolute Error (MAE):

MAE calculates the **average absolute difference** between the actual prices and the predicted prices. It gives a straightforward understanding of how much, on average, your model's predictions deviate from the actual crop prices.

Formula:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

- y_i = Actual crop price for the i^{th} data point
- $\hat{y}_i$ = Predicted crop price for the i^{th} data point
- n = Total number of data points

➢ The model compares each predicted price with the actual price.

➢ It takes the absolute value (so all differences are positive).

➢ Then, it averages these absolute differences over all data points.

2. R² Score (Coefficient of Determination)

The R² Score tells how well your model explains the variability in the actual crop prices. It measures the proportion of the variance in the dependent variable (price) that is predictable from the independent variables (features like crop, state, market, etc.).

Formula:

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}}$$

Where:

- $SS_{res} = \sum(y_i - \hat{y}_i)^2$ → Residual Sum of Squares (error between actual and predicted values)
- $SS_{tot} = \sum(y_i - \bar{y})^2$ → Total Sum of Squares (variance of actual values around the mean)

Explanation:

➢ SStot shows the total variance present in actual crop prices.

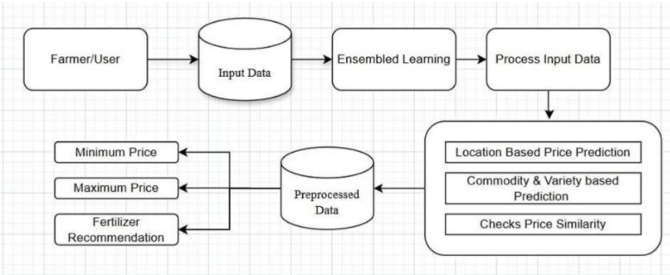
➢ SSres shows how much variance remains unexplained by the model.

➢ $R^2 = 1$: Perfect model → all variance is explained, predictions are 100% accurate.

➢ $R^2 = 0$: Model predictions are no better than simply using the mean price.

➢ $R^2 < 0$: Model performs worse than the mean.

Block Diagram:



Main Features of the Project:

1.Crop Price Prediction:

Predicts the minimum and maximum prices of crops based on user inputs such as location, commodity

Uses Ensemble Learning combining Decision Tree, Random Forest, and K- Nearest Neighbors (KNN) algorithms to improve prediction accuracy.

2.Location-Based Prediction:

Provides location-specific price predictions by analyzing historical and current market data related to the farmer's region.

3.Commodity & Variety-Based Analysis:

Offers predictions tailored to the specific crop type and variety to ensure more precise and relevant results.

4.Fertilizer Recommendation System:

Dynamically recommends suitable fertilizers if the predicted minimum price is below the threshold, helping farmers improve yield and profitability.

5.Government Scheme Suggestions:

If the predicted price is stable or profitable, it shows relevant government schemes and subsidies available to the farmer**.**

6.Data Preprocessing & Cleaning:

Handles missing values, label encoding, and normalization to ensure high- quality, clean data is fed into the model.

7.Price Similarity Check:

Cross-verifies predicted prices with historical trends or nearby market data to avoid large price deviations and provide realistic predictions.

8.Dynamic Thresholding:

Implements crop-specific price thresholds, allowing flexibility in determining when to recommend fertilizers or display schemes based on real-time market trends.

9.Evaluation Metrics Integration:

Uses Mean Absolute Error (MAE) and R^2 Score to evaluate model performance, ensuring transparency and reliability in predictions.

6.3 Government Schemes

The Government Schemes Module helps farmers access financial and technical support programs with ease. It organizes schemes in a structured table format, displaying details like scheme name, description, eligibility, and required documents. A dedicated admin panel allows authorized personnel to manage scheme information by adding new schemes, updating existing ones, and ensuring accuracy. Each scheme entry includes a unique ID, name, description, and necessary documents. Strict access controls ensure only admins can modify data, while farmers can only view it. The module integrates market analytics, enabling farmers to assess schemes alongside real-time market trends, aiding informed decision-making. Admins benefit from analytics tools to monitor scheme effectiveness and identify areas for improvement. The visually rich interface makes navigation simple, enhancing accessibility. This module boosts transparency, simplifies access to government support, and bridges the gap between policy initiatives and grassroots agricultural needs. It empowers farmers by providing timely, relevant information, helping them choose the best schemes and improve their agricultural practices.

6.4 Fertilizer Recommendation

The Fertilizer Recommendation Module helps farmers optimize crop yield and profitability by offering timely, crop-specific fertilizer guidance based on market conditions and predictive analytics. It integrates with the crop price prediction system to provide actionable insights, ensuring farmers receive the right guidance at the right time. Each crop has a predefined threshold price, calculated using historical market data, production costs, and desired profit margins. The system predicts crop prices using models like Decision Tree, Random Forest, and KNN, comparing the predicted price with the threshold value. If the predicted price is below the threshold, the module triggers personalized fertilizer recommendations to improve soil health and boost yields. Recommendations are tailored for each crop, preventing overuse or misuse of fertilizers. The threshold price is calculated as: **TP = ACP + (ACP × Desired Profit Margin %)**, where ACP is the Average Cost of Production, covering seeds, fertilizers, labor, and other inputs. This module empowers farmers with data-driven decisions, reduces risks, and promotes resource-efficient farming practices, enhancing agricultural productivity and farmer profitability.

6.5 Chatbot

The Chatbot Module provides farmers with instant, reliable support directly from the homepage, ensuring easy access without complex navigation. It delivers real-time responses on crop selection, pest control, market trends, and best farming practices, helping farmers make timely, informed decisions. Powered by Mistral AI, the chatbot understands queries conversationally and offers precise, contextually relevant answers. Farmers can quickly get insights on the best crops for each season, pest management, and current market prices. This immediate access to expert-backed information reduces reliance on external sources and minimizes risks caused by delays. The chatbot's quick guidance boosts productivity and improves farming practices. Its seamless integration with the system enhances usability for farmers of all digital literacy levels. The module empowers farmers to stay informed and make confident choices. By bridging the knowledge gap, it ensures real-time agricultural support at their fingertips.

7. RESULTS & DISCUSSIONS

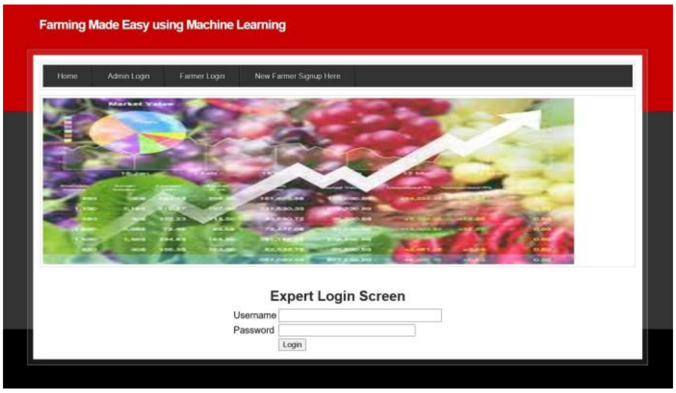


Fig 7.1 Admin Login

In Fig 7.1 The Admin Login option allows authorized administrators to securely access the backend of the platform. Through this login, admins can manage key functionalities such as adding or updating government schemes, monitoring system data, and overseeing user accounts, ensuring smooth and secure operation of the platform.

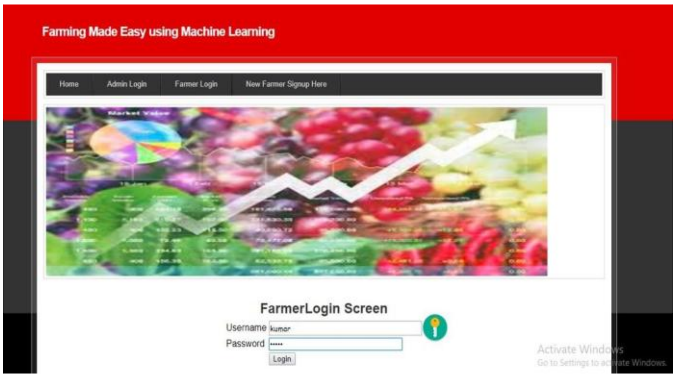


Fig 7.2 Farmer Login

In Fig7.2 The Farmer Login screen allows registered farmers to securely access personalized features like crop price predictions, fertilizer recommendations, and government schemes. By entering their username and password, farmers can manage their profiles and make informed farming decisions based on real-time data.

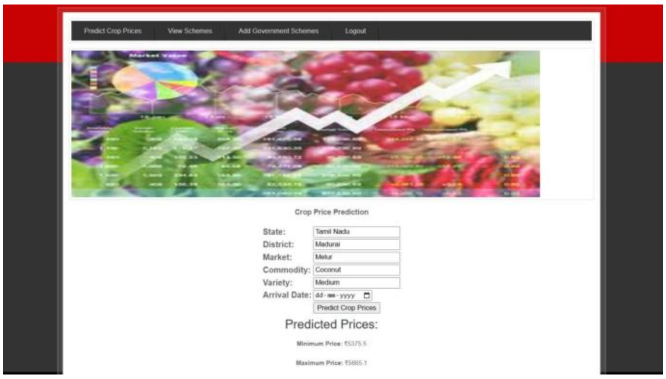


Fig 7.3 Crop price prediction

In fig 7.3 The image shows the Crop Price Prediction page where users can input details like state, district, market, crop, and variety to predict the minimum and maximum prices. It helps farmers make informed selling decisions based on predicted market trends.

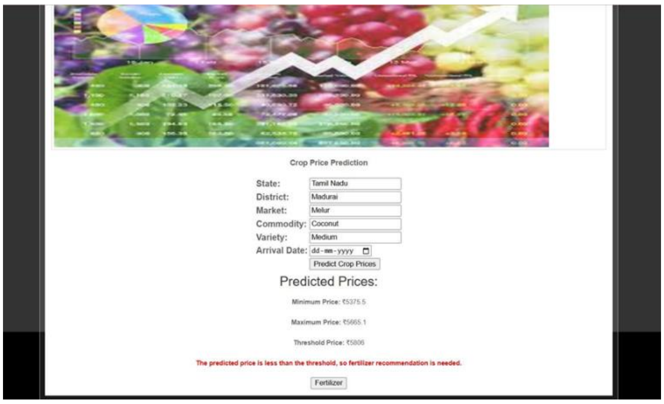


Fig 7.4 Threshold Verification

In Fig 7.4 The image shows the crop price prediction result where the predicted minimum price is compared with a threshold price. Since the predicted price is lower than the threshold, a fertilizer recommendation is provided to help improve crop profitability.

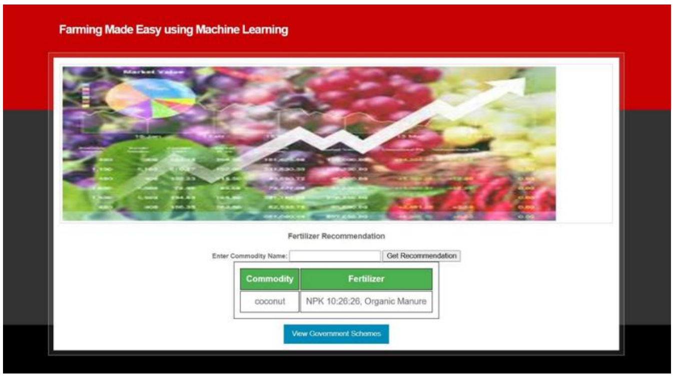


Fig 7.5 Fertilizer Recommendation

In Fig 7.5 shows a fertilizer recommendation system where users enter a crop name to receive suitable fertilizer suggestions, such as NPK 10:26:26 or Organic Manure for coconut. The system tailors recommendations to optimize crop yield and soil health. Additionally, it offers an option to explore related government schemes for further support. This ensures farmers get precise guidance and access to helpful resources.

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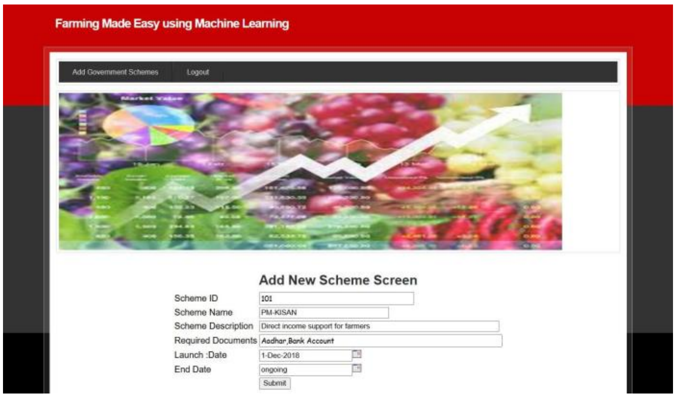

Fig 7.6 Add Schemes

In fig 7.6 The image shows an "Add New Scheme" form where administrators can input details of government schemes for farmers, including scheme ID, name, description, required documents, launch date, and end date. It is part of a farming support system aimed at integrating government scheme information.

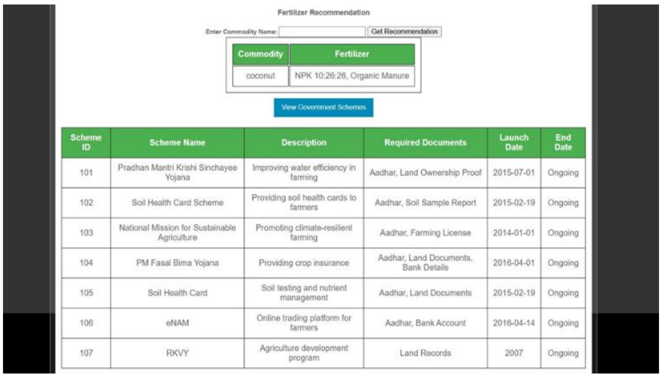

Fig 7.7 View Government Schemes

In Fig 7.7 The image displays a detailed table listing various government schemes for farmers, including their descriptions, required documents, launch dates, and status. It helps farmers access both fertilizer suggestions and beneficial schemes in one interface.

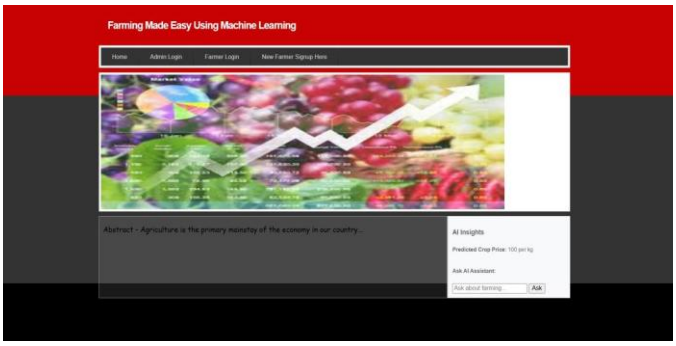

Fig 7.8 Chatbot

In Fig 7.8 The chatbot in this screen is labelled as "AI Assistant", designed to help farmers by answering farming-related queries. Users can type their questions in the input box under "Ask AI Assistant" and click the "Ask" button to receive responses, making it a useful tool for providing quick information and guidance on agricultural topics.

8. CONCLUSION

This AI-powered agricultural system provides farmers with accurate price forecasts, crop recommendations, and fertilizer suggestions, along with access to government schemes. These insights enable farmers to make well-informed decisions that enhance their productivity and profitability. By leveraging predictive analytics, the system optimizes resource usage, minimizing the wastage of water, fertilizers, and labor while improving overall efficiency. Real- time price predictions help farmers strategically plan their sales, reducing losses caused by market fluctuations and price instability. Additionally, the AI-powered chatbot offers instant expert guidance on farming practices, pest control, and market trends, making agricultural knowledge more accessible. By boosting farm profitability, reducing crop losses, and promoting sustainable practices, this system significantly contributes to India's agricultural and economic growth.

9. FUTURE ENHANCEMENTS

Integrating IoT sensors for real-time soil health and weather monitoring can significantly enhance the accuracy of crop and fertilizer recommendations, ensuring that farmers receive precise guidance based on actual field conditions. Implementing blockchain technology can provide secure and transparent transactions, helping farmers get fair prices for their produce by reducing middlemen interference and preventing fraud. Expanding the AI-powered chatbot to support multiple regional languages will improve accessibility, allowing farmers from diverse linguistic backgrounds across India to receive expert agricultural advice in their preferred language. These advancements will further strengthen the system’s impact, promoting efficiency, fairness, and inclusivity in the agricultural sector.

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