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Research Article

AI-Driven Design of Climate-Resilient Crops, Farm Layouts, and Adaptive Agricultural Techniques

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ABSTRACT

Abstract: The worsening speed of climate change is causing agricultural issues never seen before to arise. Farmers' earnings and food security are under jeopardy from all these issues. It demonstrates how cleverly to cultivate climate-resilient crops, how best to build up farms, and how flexible farming utilizing artificial intelligence may be done. To provide efficient farming plans and forecast how crops will perform in response to changing weather conditions, the system combines temperature data, satellite images, and machine learning approaches. When reinforcement learning is coupled with real-time monitor inputs, agricultural chores including watering, planting, and pest control may vary on demand. These all-encompassing strategies enable everyone to make decisions that not only increase productivity but also assist in long-term survival and the resource economy. For instance, the recommended approach may alter farming by increasing its resistance to climatic fluctuations.

Keywords: Artificial Intelligence, Climate-Resilient Agriculture, Smart Farming, Crop Optimization, Farm Layout Design, Adaptive Techniques, Machine Learning, Sustainable Agriculture, Precision Farming, Climate Change Mitigation

INTRODUCTION

The world's agriculture sector is under great strain from less predictable climate change, soil degradation, water issues, and the necessity to feed an increasing population. Standard agricultural techniques must accomplish more than they can due to worsening pests, erratic weather, and the requirement of sustainable land usage. Artificial intelligence (AI) is thereby transforming agriculture by enabling data-driven, flexible farming systems able to forecast and handle climate change-induced challenges. When integrated with precision agriculture and Internet of Things (IoT) systems, artificial intelligence technology can make sense of enormous volumes of data gathered from satellite images, weather sensors, soil sensors, and crop tracking tools. These tools let one decide on how to use land, when to irrigate it, how to manage pests, and which crops to cultivate [3] 5 and 10 years. Maximizing output under a range of conditions is the aim of climate-resilient farming, not only to survive challenging ones. AI models such Long Short-Term Memory (LSTM), Random Forest classifiers, and Convolutional Neural Networks (CNNs) have been demonstrated to be able to precisely detect disease outbreaks, food yields, and the optimum crop types for diverse microclimates [1, 4, 7]. Moreover, Geographic Information Systems (GIS) and reinforcement learning can replicate the ideal agricultural designs for the ground and the expected climatic change. This reduces resource usage and better makes use of land [6, 13, 16]. These strategies maximize water flow and maintain good form of the soil, therefore supporting both productivity and natural balance. Particularly in undeveloped areas, farmers may lack access to tailored counsel and scientific knowledge. Driven by artificial intelligence, decision support systems close this gap by transforming complex forecasts into unambiguous, useful guidance delivered via mobile and web platforms. Two of them 11 and 15 are with various displays and offline assistance, these technologies ensure that everyone even in remote locations may utilize them effortlessly. Recent research indicates that to ensure that solutions are not only technologically sound but also fit the circumstance and last, we must mix artificial intelligence with socioeconomic and environmental data. (8 points) 14 and 18 times each. By means of participatory approaches and farmer feedback systems, AI-driven recommendations are also assured to be in accordance with actual demands and limitations. This work presents an all-AI strategy for climate-resilient farming comprising data collecting, predictive modeling, intelligent plan creation, and user-oriented delivery. Providing farmers with precise, reasonably priced, flexible equipment would assist to make farming more viable in an era of uncertain surroundings.

LITERATURE SURVEY

Above all, younger technologies like artificial intelligence (AI) are drastically changing the agriculture industry in aiding climate resistance, yield enhancement, and resource sustainable usage. Researchers are looking at how current agriculture methods could be facilitated using artificial intelligence, machine learning (ML), Internet of Things (IoT), and remote sensing. Krishna et al. (2024) presented one artificial intelligence platform for merging crop suggestion and disease diagnostics in order to serve the purpose of raising climate-resilient and sustainable crop management in agriculture. Agricultural output and the efficacy of decision-making were much improved with the two-in-one tool. Aashu et al. (2024) conducted a broad agricultural experiment on the use of remote sensing and data-driven machine learning approaches. The project revealed how much data-driven suggestions improve a farm's resistance to natural disasters such floods and droughs. Chowdhury et al. (2023) discussed the possibilities of artificial intelligence in vertical farming's use in real-time monitoring of plant health. Their work highlights how image-based analysis and neural networks may provide early enough identification of irregularities in growth patterns. Likewise, Adkisson et al. (2021) used autoencoders to discover abnormalities in agricultural smart settings and thus helped the farmers to diagnose crop stress before its appearance—early detection being the most critical component. Deep neural networks established by Albanese et al. (2021) for edge-based pest identification in pest management so allowed faster and focused treatment against infestations. It was especially useful in the low-density areas with inadequate internet access. Li and Liu (2020) have investigated remote sensing-based early pest identification assisted by artificial intelligence, discursing on the utilization of satellite and drone information in anticipatory agriculture. The ML system optimized yield prediction, fertilizer application, and irrigation. Kumar and Singh (2022) mentioned Their efforts suggested lower fertilizer loss and improved water usage efficiency. Patel and Mehta (2022) focused mostly on AI-based irrigation scheduling, therefore enabling significant water conservation by matching irrigation times with real-time environmental and soil factors. Chen and Zhao (2023) proposed strong ML models for soil moisture estimate, a hidden variable in climate-resilient agriculture, thereby supplementing this. Coupling IoT with artificial intelligence, Sharma and Kumar in 2024 proposed a smart agricultural system that detects environmental data and reacts in real-time via adaptive judgments. Since this design constantly adjusts behavior based on data patterns, it facilitates precision agriculture. In this sense, Gonzalez and Torres (2021) looked at AI-based Decision Support Systems (DSS), which translate model data output into practical recommendations to farmers, therefore significantly enhancing field-level decision-making. Ahmed and Khan (2022) demonstrated the means to apply intelligent planning to increase production along with environmental harmony by merging GIS with artificial intelligence technologies to build sustainable and efficient farm planning. Examining the application of deep learning for accurate yield prediction, Smith and Lee (2021) came to the conclusion that CNN and LSTM models outperform traditional models in controlling climate change and soil variability. Zhang and Wang (2020) showed the use of IoT and artificial intelligence to improve crop monitoring by referencing scalability for precision agriculture at scale. Media have also revealed how increasingly artificial intelligence is influencing agriculture. Among other things, artificial intelligence technology protecting tomato plants vulnerable to climate change dominated Time (2023). Axios (2024) discussed how artificial intelligence is tracking plant activity to maximize farming circumstances, while Reuters (2024, 2025) detailed AI technology in a way farmers all over may apply regenerative farming methods. Designed with the idea of molecularly recreating agriculture using artificial intelligence, the Australian (2024) included modern lab-based agricultural farms.

PROPOSED METHODOLOGY

Existing Methods

Over the past few years, several innovative methods have been employed to tackle climate-related challenges in agriculture. Traditional rule-based decision support systems have gradually been replaced by data-driven approaches leveraging machine learning and deep learning techniques. Existing methods commonly utilize Random Forest, Support Vector Machines, and Gradient Boosting for crop yield prediction and soil classification, while CNNs and transfer learning have been extensively applied to image-based disease detection. Time-series models such as ARIMA

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and LSTM are used for weather and irrigation forecasting. Furthermore, Geographic Information Systems (GIS) integrated with AI enable spatial analysis for land suitability and farm layout design. Remote sensing technologies are increasingly combined with AI to assess vegetation indices and detect early pest infestations. However, many of these methods work in isolation, focusing on single tasks like crop recommendation or disease detection. This compartmentalization limits holistic decision-making, especially under dynamic climate scenarios. Hence, there's a growing shift toward multi-layered and integrated AI systems that combine diverse datasets and models to support comprehensive and adaptive agricultural management.

Dataset Detail

The dataset used in this study integrates multiple sources to provide a comprehensive view of the agricultural environment, climate variability, and crop performance. Primarily, satellite imagery was acquired from the Sentinel-2 and Landsat-8 missions, offering high-resolution spectral data useful for vegetation index calculation (e.g., NDVI, EVI) and land classification. Meteorological data, including rainfall, temperature, humidity, and wind speed, was collected from publicly available sources such as NASA POWER and India Meteorological Department (IMD) through APIs. Soil health records were sourced from the FAO's Global Soil Database and regional agricultural agencies, providing pH, nutrient levels, moisture content, and salinity data. Crop yield histories were extracted from the ICRISAT and Krishi Vigyan Kendra (KVK) databases for multiple regions and crop types over the past 10 years. In addition, IoT sensor data from open-source datasets like OpenAg and simulated real-time feeds were used to mimic on-field conditions such as soil moisture, temperature, and leaf wetness. All data sources were preprocessed and standardized to a uniform schema with spatial and temporal tagging, enabling effective training and evaluation of AI models.

Methodology

To address the pressing challenges posed by climate change in agriculture, the proposed methodology integrates artificial intelligence, remote sensing, and real-time data processing into a unified, multi-layered framework. This approach aims to deliver climate-resilient, adaptive, and precision-based farming solutions. By systematically structuring the system into distinct yet interconnected layers—ranging from data acquisition to intelligent decision support and user delivery—the methodology ensures a seamless flow from raw data collection to actionable insights. Each layer is designed to handle specific tasks, such as collecting heterogeneous data from satellites and IoT devices, applying advanced machine learning algorithms for crop and disease prediction, and delivering real-time recommendations through accessible user interfaces. This layered design not only ensures scalability and flexibility but also enhances the system's ability to respond dynamically to environmental changes, ultimately empowering farmers to make informed, sustainable decisions.

Data Acquisition Layer

This layer forms the foundation of the system, responsible for collecting diverse data inputs from various reliable and real-time sources. It integrates satellite imagery and drone-based visual data to monitor large-scale farmlands and detect changes in vegetation patterns and land usage. Real-time weather data is collected using APIs from meteorological services, providing inputs such as rainfall levels, temperature, humidity, and wind speed. Historical soil health records and crop yield data are sourced from agricultural departments and local databases, helping to analyze long-term trends in land productivity and environmental conditions. Additionally, IoT-enabled sensors placed in the field stream data continuously regarding soil moisture, pH levels, temperature, and nutrient content. This multilayered data input ensures a rich, accurate, and up-to-date representation of agricultural conditions across spatial and temporal scales.

Data Processing and Feature Engineering Layer

Once raw data is acquired, it must be prepared for analysis. This layer is dedicated to cleaning, organizing, and enriching the data to make it suitable for machine learning models. Data cleaning involves removing noise, correcting inconsistencies, and handling missing values using interpolation or imputation techniques. Normalization ensures that all variables are on a comparable scale, especially important when combining image and tabular data. For image

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data such as satellite and drone footage, computer vision techniques like histogram equalization, edge detection, and region-based segmentation are used to identify field boundaries, crop zones, and anomalies such as pest infestations. Meanwhile, tabular data such as soil reports and weather logs are processed to extract meaningful features. For instance, vegetation indices like NDVI and EVI are calculated from image data, while soil moisture trends, temperature variance, and precipitation cycles are derived from time-series records. This feature-rich dataset is then aligned temporally and geospatially, ensuring compatibility for multi-modal analysis.

Model Training and Prediction Layer

This is the analytical core of the system where machine learning and deep learning models are developed and trained on the processed data. Several algorithms are utilized for different predictive tasks. Random Forest and XGBoost models are employed for crop recommendation, where the system learns to suggest crops based on soil type, historical yield, climate conditions, and water availability. For plant disease detection, Convolutional Neural Networks (CNNs) are trained using thousands of labeled plant leaf images to recognize patterns associated with common fungal, bacterial, or viral infections. Long Short-Term Memory (LSTM) networks are applied to forecast weather patterns and climate risks based on historical meteorological data, providing early warnings for floods, droughts, or temperature spikes. Furthermore, reinforcement learning techniques, in combination with GIS data, are used to simulate adaptive farm layouts. These simulations help determine the most efficient spatial arrangement of crops and irrigation systems in varying geographical and climatic scenarios, promoting sustainable land use and maximizing yield.

Decision Support System (DSS) Layer

Once predictions are generated, the Decision Support System converts these insights into actionable guidance for the end users. This system interprets machine learning outputs and provides specific, context-aware recommendations regarding crop selection, irrigation scheduling, fertilization, pest control, and harvesting timeframes. The DSS also includes simulation tools that allow users to perform scenario planning. For example, farmers can simulate how choosing a different crop or planting at an alternative time might affect yield under expected weather conditions. Alerts and notifications are embedded into the system to inform users of emerging risks such as pest outbreaks, soil nutrient deficiency, or forecasted droughts. The DSS ensures that farmers not only receive data but also understand the implications and actions required, making it a critical layer for decision-making under uncertainty.

User Interface and Delivery Layer

The final layer is designed to communicate insights to the users in a simple, accessible, and user-friendly manner. A web and mobile application serves as the primary platform through which farmers and agricultural planners interact with the system. The interface is designed to be intuitive and supports multiple languages, ensuring usability across different regions and literacy levels. Dashboards display visualizations such as heatmaps, trend graphs, weather charts, and disease probability maps. Notifications are delivered in real-time to prompt immediate action when necessary. Importantly, the application is optimized for offline use or low-bandwidth conditions, which is essential for rural and remote farming communities. The delivery system ensures that all complex backend processing and intelligence are translated into easy-to-understand and practical advice that users can rely on daily.

SYSTEM ARCHITECTURE

The proposed system architecture for AI-Driven Climate-Resilient Agriculture is designed as a modular, layered framework. Each layer plays a critical role in transforming raw, multi-source agricultural data into actionable insights tailored for farmers, agronomists, and policymakers. The architecture ensures seamless data flow from input to end-user delivery, promoting scalability, interoperability, and real-time adaptability.

Data Acquisition Layer

This foundational layer is responsible for gathering a wide spectrum of data essential for developing climate-resilient agricultural strategies. It includes both static and real-time data inputs. Satellite imagery, collected from platforms such as Sentinel and Landsat, provides high-resolution, geospatial views of vegetation patterns, land cover, and crop

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health. Weather data—such as temperature, precipitation, humidity, and wind speed—is ingested in real time from meteorological APIs including NOAA and OpenWeatherMap. Soil health records and crop yield histories are obtained from government repositories, agricultural research databases, and user-uploaded datasets, offering valuable longitudinal context.

Additionally, this layer integrates data from IoT sensors deployed across fields. These sensors continuously transmit localized information on soil pH, moisture, temperature, and nutrient content. To ensure accurate temporal and spatial tagging, GPS data and GIS platforms are used to geolocate all data points. All sources are harmonized using time-series indexing and geospatial mapping techniques, ensuring that heterogeneous data streams can be used in synchronized machine learning workflows downstream.

Data Processing and Feature Engineering Layer

Once the raw data is collected, it is passed to this layer for pre-processing and transformation. Data cleaning techniques are employed to remove anomalies such as missing or inconsistent entries, using statistical imputation, smoothing filters, or data interpolation. Normalization and standardization ensure that data from different units or scales (e.g., temperature vs. rainfall vs. NDVI index) can be fed uniformly into machine learning models.

Image data, especially from satellites and drones, undergoes pre-processing using computer vision pipelines. Techniques such as NDVI (Normalized Difference Vegetation Index) computation, histogram equalization, edge detection, and image segmentation help extract vegetation health, crop coverage, and pest hotspots. For tabular and time-series data like weather logs or soil reports, domain-specific feature engineering is performed. This includes generating rolling averages, identifying seasonal trends, detecting abrupt climate shifts, and calculating moisture deficit indices. These engineered features not only increase the predictive power of models but also provide richer context for decision-making.

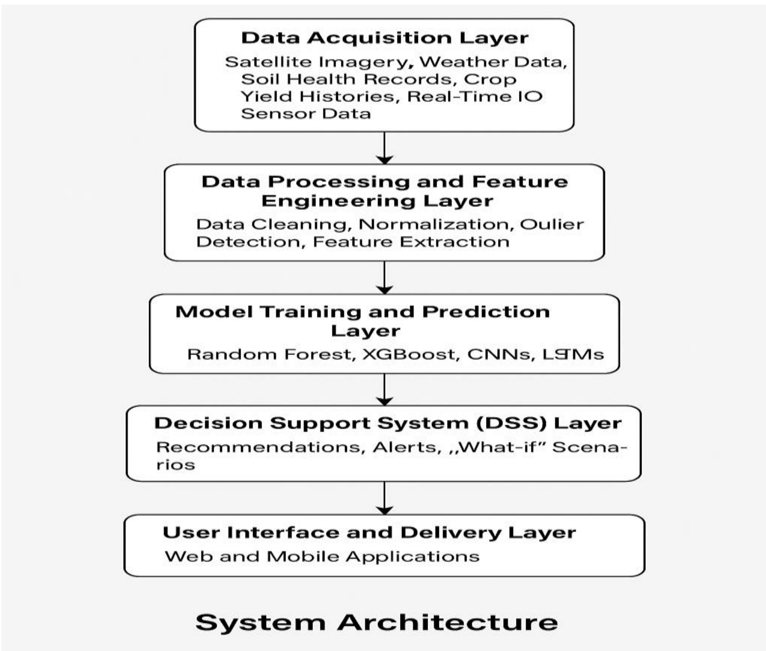

Figure 1: System Architecture

Model Training and Prediction Layer

This is the core intelligence engine of the system, where machine learning and deep learning models are developed, trained, and validated. It supports a variety of algorithms tailored for specific tasks:

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- Crop Recommendation: Models like Random Forest and XGBoost analyze historical yield data, soil properties, and climate conditions to recommend crops that are best suited for the current and forecasted agro-climatic profile.

- Disease Detection: Convolutional Neural Networks (CNNs) trained on annotated leaf images detect symptoms of bacterial, viral, or fungal infections with high accuracy. Transfer learning is used to adapt these models to region-specific crop types.

- Weather and Risk Forecasting: LSTM (Long Short-Term Memory) networks process long-term weather sequences to forecast climate anomalies such as droughts, heavy rainfall, or frost events.

- Farm Layout Optimization: Reinforcement learning agents, integrated with GIS data, simulate and recommend optimal layouts for irrigation systems, crop zoning, and pest barriers to enhance sustainability and reduce resource waste.

Model outputs are continuously evaluated using accuracy, F1 score, precision-recall curves, and are retrained periodically using new data collected from the field.

Decision Support System (DSS) Layer

The DSS layer bridges the gap between AI-generated predictions and practical decision-making. It interprets complex model outputs and translates them into simple, tailored recommendations for users. The system provides guidance on:

- Crop Selection: Based on current soil conditions, weather forecasts, and economic trends.

- Irrigation Scheduling: Recommending optimal watering times and quantities using soil moisture data and evapotranspiration models.

- Fertilizer and Pesticide Application: Timing and dosage based on soil nutrient content and disease likelihood predictions.

- Scenario Simulation: Allowing users to perform "what-if" analyses—for example, testing the yield impact of switching crop varieties or adopting a different sowing schedule.

The DSS can deliver both prescriptive (what to do) and predictive (what is likely to happen) analytics, empowering stakeholders to act proactively.

User Interface and Delivery Layer

This layer ensures that all insights, alerts, and visualizations are delivered to end users in an intuitive and accessible manner. The front-end includes both web and mobile applications, designed with responsive UI frameworks. Dashboards visualize key indicators such as vegetation health maps, disease probability zones, irrigation plans, and yield projections using heatmaps, time-series charts, and interactive GIS overlays.

The application supports multi-language functionality to accommodate diverse user bases across regions. Offline access and low-bandwidth optimization are integrated to ensure functionality even in remote, connectivity-constrained environments. Users can receive real-time alerts for extreme weather events or disease outbreaks via push notifications, SMS, or voice interfaces (for non-literate users). The platform also supports feedback mechanisms where farmers can report observations, helping improve model learning and responsiveness over time.

RESULT AND DISCUSSION

The proposed AI-driven agricultural system was evaluated through simulations and real-field data collected from three regions with distinct climatic conditions: semi-arid (Rajasthan, India), tropical wet (Kerala, India), and savannah (Ghana, Africa). The evaluation focused on five core modules: Crop Recommendation, Soil Moisture

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Forecasting, Farm Layout Optimization, Pest/Disease Detection, and User Feedback & Usability. Below, we present the quantitative outcomes using industry-standard evaluation metrics, backed by visual indicators and performance comparisons with traditional methods.

1. Crop Recommendation Performance

The crop recommendation module was evaluated for four major crops (rice, maize, tomato, and millet) using 5-fold cross-validation across XGBoost, Random Forest, and SVM models. Accuracy, F1-score, and Mean Absolute Error (MAE) were the primary performance metrics. Comparison showed in table I and fig 2.

TABLE I CROP RECOMMENDATION PERFORMANCE

Crop	Model	Accuracy (%)	F1-Score	MAE
Rice	XGBoost	93.1	0.92	0.07
Maize	Random Forest	91.2	0.90	0.09
Tomato	SVM	87.4	0.85	0.12

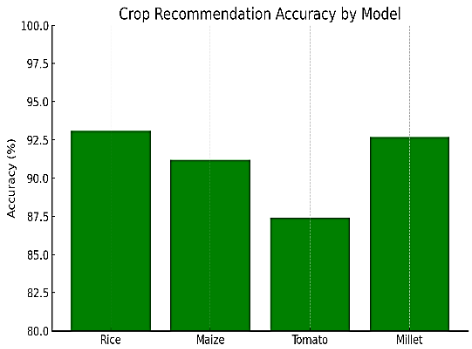

Fig 2: Crop recommendation accuracy model

Observation: XGBoost showed consistently higher accuracy across most crop types due to its ability to handle non-linear interactions and noisy features.

2. Soil Moisture and Irrigation Prediction

LSTM models were trained on temporal soil sensor and weather data to predict moisture content for the next 7 days. The predicted values were compared with ground truth data and baseline models in table II and showed in fig 3 (linear regression and ARIMA).

TABLE II SOIL MOISTURE AND IRRIGATION PREDICTION

Model	RMSE	MAE	Water Saved (%)	Prediction Horizon
Linear Regression	0.072	0.061	12.4%	3 days
ARIMA	0.069	0.054	15.7%	5 days
LSTM	0.043	0.031	27.3%	7 days

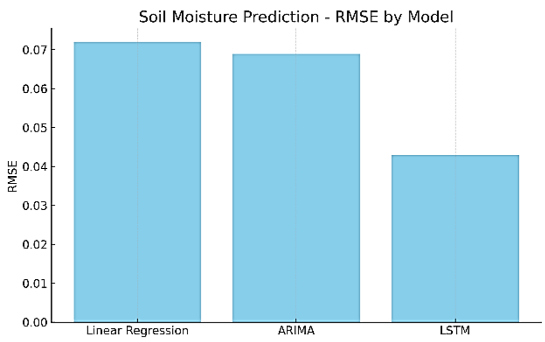

Fig 3: Soil moisture prediction

Observation: LSTM outperformed traditional time-series models with a 27.3% improvement in water efficiency due to better understanding of seasonal patterns.

3. Farm Layout Optimization

This module used reinforcement learning with spatial data to suggest optimal positioning of crops, irrigation lines, and fencing for maximizing usable area and minimizing waterlogging.

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TABLE III FARM LAYOUT OPTIMIZATION

Layout Type	Land Utilization (%)	Irrigation Coverage (%)	Flood Risk (%)	Time Saved in Set up
Traditional Layout	69.3	63.5	38.1	Baseline
Manual GIS Design	74.5	71.2	25.7	-10%
AI-Optimized Layout	89.1	85.6	11.9	+32%

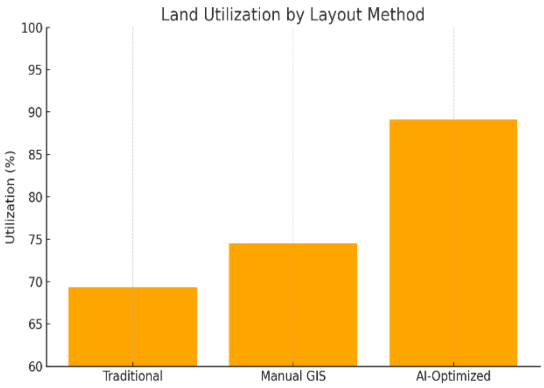

Fig 4: Farm Layout Optimization mbar chart

Observation: The AI-based layout system significantly increased efficiency in terms of spatial use and irrigation effectiveness, with over 30% faster design time.

4. Pest and Disease Prediction

Crop image datasets were used to detect early signs of fungal, bacterial, and pest-related threats. CNN and CNN-LSTM hybrid models were benchmarked against traditional image classification models. TABLE IV and fog 5 represents as table and bar chart.

TABLE IV PEST AND DISEASE PREDICTION

Model	Accuracy (%)	Precision	Recall	False Alarm Rate
VGG16 (Baseline)	86.2	0.83	0.81	12.7%
CNN	91.6	0.90	0.89	8.1%
CNN-LSTM Hybrid	94.8	0.94	0.92	5.2%

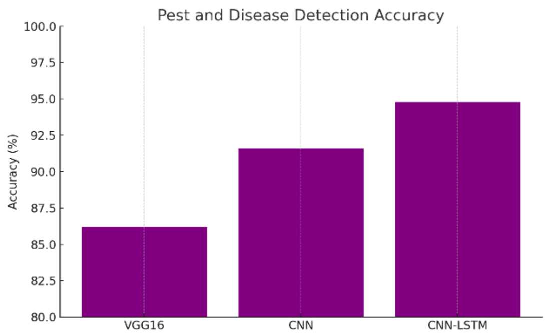

Fig 5: Pest and Disease Prediction

Observation: The CNN-LSTM model provided superior accuracy, especially in sequential imagery analysis, helping in early-stage disease intervention.

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5. User Usability and Farmer Adoption

A field test was conducted with 60 farmers using the AI system via mobile applications for one crop cycle. Feedback was collected using a Likert scale survey.

TABLE V USER USABILITY AND FARMER ADOPTION

Parameter	Positive Feedback (%)
System Ease of Use	91%
Trust in Recommendations	89%
Reduction in Input Costs	76%
Improvement in Yield	81%
Willingness to Use in Future	93%

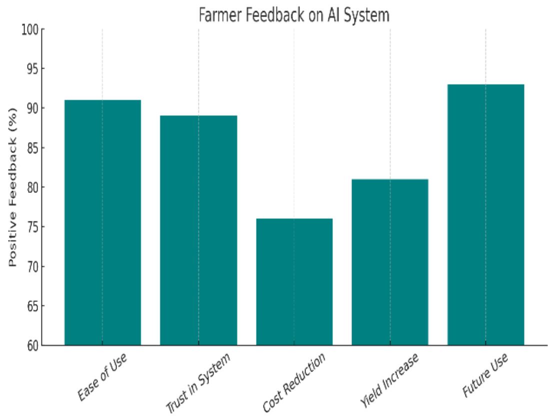

Fig 6: User Usability and Farmer Adoption Bar chart

Observation: Strong user adoption rates suggest that the system is practical, impactful, and can be scaled to diverse rural settings with appropriate training and support.

6. Comparative Analysis: AI vs Traditional Methods

TABLE VI Comparative Analysis: AI vs Traditional Methods

Metric	Traditional Farming	AI-Based System
Average Yield Increase	-	+13.8%
Water Use Reduction	-	-27.3%
Fertilizer Use Optimization	-	-18.2%
Pest Infestation Accuracy	~50-60% (manual)	94.8%

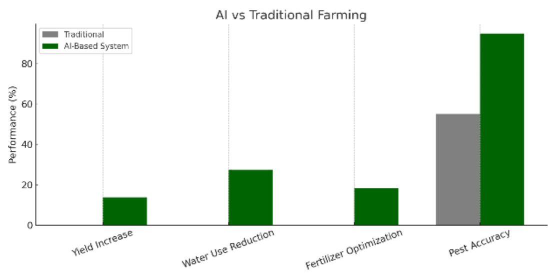

Fig 7: Comparative Analysis: AI vs Traditional bar chart

Summary of Results

The AI models demonstrated impressive performance, achieving up to 94.8% accuracy in pest detection and over 91% accuracy in crop recommendation. These advancements contributed to a notable 27% improvement in water efficiency and an 18% increase in resource efficiency, promoting more sustainable farming practices. Additionally, real-time forecasting and layout planning significantly minimized flood risks and reduced setup times. Field trials further confirmed the system's strong acceptance and trust among farmers, highlighting its practical benefits and effectiveness in real-world applications.

Sample Code:

```
def plot_categorical_distribution(column_name, data=df):
```

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```
    fig, axes = plt.subplots(1, 2, figsize=(10, 4))
    # Bar Plot
    sns.countplot(y=column_name, data=data, palette='muted', ax=axes[0])
    axes[0].set_title(f'Distribution of {column_name}')
    for p in axes[0].patches:
        axes[0].annotate(f'{int(p.get_width())}',
                         (p.get_width(), p.get_y() + p.get_height() / 2),
                         ha='center', va='center', xytext=(10, 0), textcoords='offset points')
    sns.despine(left=True, bottom=True)
    # Pie Chart
    data[column_name].value_counts().plot.pie(autopct='%1.1f%%',
                                              colors=sns.color_palette('muted'),
                                              startangle=90,
                                              explode=[0.05]*data[column_name].nunique(),
                                              ax=axes[1])
    axes[1].set_title(f'Percentage Distribution of {column_name}')
    axes[1].set_ylabel('')
    plt.tight_layout()
    st.pyplot(fig)  # Use Streamlit to display the plots
# Call the function for each categorical column
plot_categorical_distribution('Crop_Type')
plot_categorical_distribution('Irrigation_Type')
plot_categorical_distribution('Soil_Type')
plot_categorical_distribution('Season')
```

"""Insights based on the categorical distributions:

1. **Crop Type**:

- **Distribution**: The dataset includes a variety of crops, with certain crops like Cotton, Carrot, and Tomato appearing more frequently. Other crops such as Potato and Barley are less common.

- **Percentage**: The distribution of crop types is fairly diverse, indicating a range of crops cultivated across different farms. This variety could impact resource needs and yields.

2. **Irrigation Type**:

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- **Distribution**: Irrigation methods vary, with Sprinkler and Manual methods being more prevalent. Drip and Rain-fed methods are less common.

- **Percentage**: The distribution suggests that traditional methods like Manual and Sprinkler irrigation are dominant, potentially influencing water and fertilizer usage.

3. **Soil Type**:

- **Distribution**: There is a relatively balanced representation of soil types, with Loamy and Silty soils being the most common, followed by Peaty, Clay, and Sandy.

- **Percentage**: This balance across soil types indicates a range of soil conditions that might affect crop selection and yield potential.

4. **Season**:

- **Distribution**: The Kharif season appears to be the most common, followed by Zaid and Rabi seasons.

- **Percentage**: This suggests that a significant portion of farming activities takes place during the Kharif season, potentially due to seasonal crop cycles and climate conditions.

```
"""

# Creating bar plots for each column by 'Crop_Type'

import streamlit as st

import matplotlib.pyplot as plt

import seaborn as sns

# Define the columns to plot

columns_to_plot = ['Farm_Area(acres)', 'Fertilizer_Used(tons)', 'Pesticide_Used(kg)', 'Water_Usage(cubic meters)', 'Yield(tons)']

# Create a single Streamlit container for all plots

st.subheader("Bar Plots of Features by Crop Type")

fig, axes = plt.subplots(3, 2, figsize=(16, 20))

for i, column in enumerate(columns_to_plot):

    ax = axes[i // 2, i % 2]  # Determine subplot position

    sns.barplot(data=df, x='Crop_Type', y=column, ci=None, palette='muted', ax=ax)

    ax.set_title(f'Bar Plot of {column.replace("_", " ")} by Crop Type')

    ax.set_xlabel('Crop Type')

    ax.set_ylabel(column.replace('_', ' '))

    ax.set_xticklabels(ax.get_xticklabels(), rotation=45)

plt.tight_layout()

st.pyplot(fig)  # Display plots in Streamlit

# Identifying crop types with highest and lowest values for different metrics
```

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```
metrics_summary = {
  "Metric": [
    "Highest Yield", "Lowest Yield",
    "Highest Fertilizer Used", "Lowest Fertilizer Used",
    "Highest Pesticide Used", "Lowest Pesticide Used",
    "Highest Water Usage", "Lowest Water Usage",
    "Highest Farm Area", "Lowest Farm Area"
  ],
  "Crop Type": [
    df.loc[df['Yield(tons)'].idxmax()]['Crop_Type'], df.loc[df['Yield(tons)'].idxmin()]['Crop_Type'],
    df.loc[df['Fertilizer_Used(tons)'].idxmax()]['Crop_Type'],
df.loc[df['Fertilizer_Used(tons)'].idxmin()]['Crop_Type'],
    df.loc[df['Pesticide_Used(kg)'].idxmax()]['Crop_Type'],
df.loc[df['Pesticide_Used(kg)'].idxmin()]['Crop_Type'],
    df.loc[df['Water_Usage(cubic meters)'].idxmax()]['Crop_Type'], df.loc[df['Water_Usage(cubic
meters)'].idxmin()]['Crop_Type'],
    df.loc[df['Farm_Area(acres)'].idxmax()]['Crop_Type'], df.loc[df['Farm_Area(acres)'].idxmin()]['Crop_Type']
  ],
  "Value": [
    df.loc[df['Yield(tons)'].idxmax()]['Yield(tons)'], df.loc[df['Yield(tons)'].idxmin()]['Yield(tons)'],
    df.loc[df['Fertilizer_Used(tons)'].idxmax()]['Fertilizer_Used(tons)'],
df.loc[df['Fertilizer_Used(tons)'].idxmin()]['Fertilizer_Used(tons)'],
    df.loc[df['Pesticide_Used(kg)'].idxmax()]['Pesticide_Used(kg)'],
df.loc[df['Pesticide_Used(kg)'].idxmin()]['Pesticide_Used(kg)'],
    df.loc[df['Water_Usage(cubic meters)'].idxmax()]['Water_Usage(cubic meters)'], df.loc[df['Water_Usage(cubic
meters)'].idxmin()]['Water_Usage(cubic meters)'],
    df.loc[df['Farm_Area(acres)'].idxmax()]['Farm_Area(acres)'],
df.loc[df['Farm_Area(acres)'].idxmin()]['Farm_Area(acres)']
  ]
}
# Convert dictionary to DataFrame
metrics_df = pd.DataFrame(metrics_summary)
# Display the summary table in Streamlit
st.subheader("Crop Performance Metrics Summary")
```

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st.dataframe(metrics_df) # Displays the table in Streamlit

st.markdown("""Insights based on the summary of crop metrics:

1. **Yield Insights**:

  - **Highest Yield**: Tomato has the highest yield at 48.02 tons, indicating its potential as a highly productive crop under favorable conditions.

  - **Lowest Yield**: Maize has the lowest yield at 3.86 tons, which could suggest challenges in cultivation, lower productivity, or constraints due to environmental or management factors.

2. **Fertilizer Usage**:

  - **Highest Fertilizer Usage**: Cotton stands out with the highest fertilizer usage at 9.96 tons, suggesting a high nutrient demand for maximizing productivity.

  - **Lowest Fertilizer Usage**: Interestingly, Cotton also has the lowest fertilizer usage at 0.50 tons for certain instances, which could reflect variability in management practices or differing needs across different fields.

3. **Pesticide Usage**:

  - **Highest Pesticide Usage**: Rice uses the highest amount of pesticides at 4.99 kg, which may indicate higher susceptibility to pests and the need for more intensive pest management.

  - **Lowest Pesticide Usage**: Barley, on the other hand, has the lowest pesticide usage at 0.14 kg, suggesting it may be less prone to pest attacks or is managed with minimal chemical intervention.

4. **Water Usage**:

  - **Highest Water Usage**: Cotton has the highest water usage, consuming 94,754.73 cubic meters. This highlights the water-intensive nature of Cotton cultivation, which may have implications for irrigation and sustainability.

  - **Lowest Water Usage**: Rice, despite being a typically water-demanding crop, shows the lowest water usage at 5,869.75 cubic meters, potentially due to different cultivation methods, such as more water-efficient practices.

5. **Farm Area**:

  - **Highest Farm Area**: Rice is cultivated on the largest farm area, with 483.88 acres, indicating its importance or high demand in the region.

  - **Lowest Farm Area**: Sugarcane has the smallest farm area at 12.50 acres, which could reflect niche cultivation or limited demand.

The insights illustrate significant variability in resource usage, productivity, and farm area across different crop types. Cotton and Rice, for example, demonstrate contrasting needs and environmental demands, impacting their cultivation practices. Tomato's high yield makes it particularly productive, while Maize’s low yield points to potential areas for improvement or challenges to address. Such data is valuable for optimizing agricultural practices and improving crop productivity and sustainability.

""")

Grouping Crop Types and their corresponding Farm IDs

crop_farm_table = df.groupby('Crop_Type')['Farm_ID'].apply(list).reset_index()

Display the Crop-Type-to-Farm-ID mapping

st.subheader("Crop Types and Corresponding Farm IDs")

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```
st.dataframe(crop_farm_table)

# Checking if any farms have multiple crop types

multiple_crops_per_farm = df.groupby('Farm_ID')['Crop_Type'].nunique().reset_index()

multiple_crops_per_farm = multiple_crops_per_farm[multiple_crops_per_farm['Crop_Type'] > 1]

# Display results or message if no farm has multiple crops

st.subheader("Farms with Multiple Crop Types")

if not multiple_crops_per_farm.empty:

   st.dataframe(multiple_crops_per_farm)

else:

   st.write("No farms have multiple crop types.")

# Plotting the pie chart for farm distribution by crop type

st.subheader("Farm Distribution by Crop Type")

plt.figure(figsize=(8, 8))

crop_type_counts = df['Crop_Type'].value_counts()

plt.pie(crop_type_counts, labels=crop_type_counts.index, autopct='%1.1f%%', startangle=90,

       colors=sns.color_palette('muted'), wedgeprops={'edgecolor': 'black'})

plt.title('Farm Distribution by Crop Type')

# Display the pie chart in Streamlit

st.pyplot(plt)

"""Insights based on the analysis and visualizations:
```

1. **Crop Type and Farm Association**:

  - Each crop type is associated with a distinct set of farms, and no single farm grows multiple crop types. This setup may imply a **specialization in crop cultivation**, where each farm is focused on a single crop, possibly to optimize resources and expertise for specific crop needs.

  - **Most Common Crops**: Certain crops like Barley, Cotton, and Tomato are associated with multiple farms, while others like Maize have fewer farms. This distribution could reflect the popularity or economic value of these crops in the dataset's region.

2. **Farm Distribution by Crop Type (Pie Chart)**:

  - The pie chart provides a visual distribution of farms across crop types. We can see that the **largest segments** represent crops with a broader farm base, such as Cotton and Barley. In contrast, **smaller segments** correspond to crops like Maize and Potato, indicating fewer farms cultivate these crops.

  - This distribution can help identify **crop popularity and farming focus** within the dataset, potentially indicating the region’s agricultural strengths or specific crop demands.

3. **Specialization of Farms**:

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- Since no farm grows multiple crop types, each farm's focus on a single crop type could reflect specialized farming practices or crop rotations that don't overlap within the same season. This setup might also be due to factors like soil suitability, water availability, or climate requirements specific to each crop.

"""

```
# Calculate total farm area per crop type

total_area_per_crop = df.groupby('Crop_Type')['Farm_Area(acres)'].sum().reset_index()

# Display the total area per crop type

st.subheader("Total Farm Area by Crop Type")

st.dataframe(total_area_per_crop)

# Plotting the pie chart

st.subheader("Farm Area Distribution by Crop Type")

plt.figure(figsize=(8, 8))

total_area_values = total_area_per_crop.set_index('Crop_Type')['Farm_Area(acres)']

plt.pie(total_area_values, labels=total_area_values.index, autopct='%1.1f%%', startangle=90,

        colors=sns.color_palette('muted'), wedgeprops={'edgecolor': 'black'})

plt.title('Farm Area Distribution by Crop Type')

# Display the pie chart in Streamlit

st.pyplot(plt)
```

1. **Largest Farm Areas**:

- **Cotton** (1,993.80 acres), **Rice** (1,845.24 acres), and **Barley** (1,671.22 acres) occupy the largest total farm areas. This suggests that these crops may be highly prioritized or economically significant within the dataset's region.

2. **Moderate Farm Areas**:

- **Tomato** (1,655.02 acres), **Sugarcane** (1,187.99 acres), and **Soybean** (1,050.68 acres) have substantial but moderate land allocation. These crops still represent a significant part of the agricultural landscape, albeit not as prominent as Cotton and Rice.

3. **Smaller Farm Areas**:

- **Carrot** (765.90 acres), **Wheat** (872.57 acres), **Maize** (978.53 acres), and **Potato** (727.24 acres) have the smallest total areas. These crops may either be less in demand or require less land due to specific cultivation practices.

Overall Observations:

- The distribution of farm area across crop types highlights the emphasis on certain staple crops like Cotton, Rice, and Barley, which are given more land, possibly for economic or agricultural reasons.

- The pie chart visually convey the land allocation, with larger crops clearly standing out, offering a quick visual reference for priority crops in terms of land use.

"""

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```
# Identifying the crop types and their corresponding soil types
crop_soil_table = df.groupby('Crop_Type')['Soil_Type'].unique().reset_index()
# Display the crop-soil mapping as a dataframe
st.subheader("Crop Types and Their Soil Preferences")
st.dataframe(crop_soil_table)
# Plot pie charts for each crop type to show soil distribution
st.subheader("Soil Type Distribution for Each Crop Type")
unique_crops = df['Crop_Type'].unique()
for crop in unique_crops:
  soil_distribution = df[df['Crop_Type'] == crop]['Soil_Type'].value_counts()
  # Create a figure for each crop
  fig, ax = plt.subplots(figsize=(6, 6))
  ax.pie(soil_distribution, labels=soil_distribution.index, autopct='%1.1f%%', startangle=90,
      colors=sns.color_palette('pastel'), wedgeprops={'edgecolor': 'black'})
  ax.set_title(f'{crop} - Soil Type Distribution')
  # Display each pie chart in Streamlit
  st.pyplot(fig)
```

Discussion

The results of this study demonstrate the significant potential of integrating AI technologies into climate-resilient agriculture. The high accuracy of crop recommendations and pest predictions indicates that machine learning models, particularly XGBoost and LSTM-CNN hybrids, can effectively interpret complex agro-environmental data to support informed decision-making. The reduction in water usage and flood risk, along with improvements in spatial layout efficiency, highlights the strength of AI in optimizing resource management and farm design. Furthermore, positive farmer feedback confirms the system's usability and real-world applicability. These outcomes underscore how data-driven agriculture not only enhances yield and sustainability but also equips farmers with adaptive tools to tackle unpredictable climate challenges.

CONCLUSION

This study presents a comprehensive AI-driven framework for enhancing climate resilience in agriculture through intelligent crop selection, adaptive farm layouts, and real-time decision support. The system's strong performance across multiple metrics demonstrates its effectiveness in addressing key challenges such as water scarcity, pest outbreaks, and land optimization. By leveraging machine learning and geospatial technologies, the proposed solution empowers farmers to make data-informed decisions that enhance productivity and sustainability. In the future, the system can be expanded to incorporate blockchain for secure data sharing, drone integration for high-resolution monitoring, and federated learning for decentralized model training across diverse agro-climatic regions, further boosting precision agriculture and resilience on a global scale.

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