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REVOLUTIONIZING AGRICULTURE: SMART FARMING USING MACHINE AND DEEP LEARNING

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Abstract— **This Study explores how machine learning (ML) and deep learning (DL) are revolutionizing agriculture, especially in crop prediction and disease detection. The proposed system presents a Smart Farming system powered by AI that is based on integrating machine learning (ML) and deep learning (DL) technologies to transform farm practices. The framework utilizes ML algorithms to read soil characteristics, climate conditions, and weather forecasting for precise prediction of crops, while DL models leverage image-based disease detection algorithms to detect diseases in plants at high accuracy levels. By transforming heterogeneous data sets of soil parameters, climate information, and crop images, important features like soil pH, nutrient content, and leaf status are designed to enhance model performance. The system is focused on real-time monitoring and AI-based suggestions, with the aim of detecting diseases at an early stage and selecting the best crops. Experimental outcomes show improved accuracy and responsiveness over conventional agriculture practices, lowering losses and increasing agricultural productivity significantly. This multi-dimensional strategy not only enhances farmer decision-making but also sets a new standard in smart farming, encouraging sustainability, efficiency, and resilience in contemporary agriculture.**

Keywords— **Machine Learning, Deep Learning, Smart Farming, Image Processing, Disease Detection.**

I. INTRODUCTION

Agriculture is the main industry that provides the backbone of the Indian economy, providing employment to a large number of individuals and ensuring food security. More than 60% of Indian land is used for agriculture to feed 1.3 billion people [1]. Traditional farming is experience-based decision-making, where farmers choose crops based on local trends, past experience, or neighboring fields. This approach is sure to lead to inefficient crop selection, no crop rotation, loss of soil nutrients, and lower yields, eventually leading to soil pollution and degradation [2]. To overcome these limitations, technology-based solutions such as machine learning (ML) and artificial intelligence (AI) have been used in agriculture, offering a data-driven solution to crop prediction, yield forecasting, and plant disease detection [3].

Machine learning has been a game-changer for precision agriculture through the application of big data analytics, IoT-based sensors, and high-performance computing for optimization of crop selection, soil fertility management, and resource utilization [4]. Compared to conventional methods, ML algorithms analyze environmental and soil factors like nitrogen (N), phosphorus (P), potassium (K), pH, rainfall, temperature, and humidity to deliver the most suitable crop for a piece of land [5]. The system presented in this paper employs Support Vector Machine (SVM) and Decision Tree algorithms for identification of agricultural data patterns and information on crop selection, nutrient management, yield estimation (q/acre), seed requirement (kg/acre), and market price prediction [6].

Along with crop prediction, plant leaf-based disease diagnosis using deep learning (DL) methods is a crucial part of intelligent agriculture. Convolutional Neural Networks (CNNs) and image processing methods enable plant leaf-based disease diagnosis automatically without the need for humans, for early plant infection detection. This method enables manual inspection dependency reduction, minimizes crop loss, and increases farm productivity overall [7].

This paper strives to assess the impact of crop prediction and yield forecasting machine learning models and deep learning-based plant disease detection. The study integrates real-time environmental data from **V C Farm Mandya, government websites, and weather outlets** to enhance agricultural decision-making and yield actionable knowledge for farmers [8].

II. LITERATURE REVIEW

Agricultural development has historically been linked to population growth and economic prosperity. Early farming, dating back to 11,000 years ago, employed empirical observations and traditional knowledge to choose crops and forecast yields [9]. Over time, scientific developments such as mechanized farming, fertilization techniques, and statistical models improved agricultural output. In particular, the Haber-Bosch process, developed in the 1900s, revolutionized nitrogen fertilization, and this has been attributed to the world population explosion from 1.6 billion to 7.7 billion [10].

The use of statistical models in agriculture, for example, regression analysis, was a significant contribution to crop forecasting. In the 1920s, R.A. Fisher promoted the use of statistical techniques in agriculture, and by 1925, the Cobb-Douglas Function was used to measure agricultural productivity [11]. Regression models employ past crop yields, climatic patterns, and soil characteristics to predict future yields. However, traditional linear regression models are not perfect because they are site-specific and fail to account for the non-linear relationships between soil nutrients, climatic variation, and crop productivity [12].

Recent machine learning advancements have bridged these challenges using the application of advanced predictive algorithms. Deep learning (DL) and convolutional neural networks (CNNs) have been successful in providing robust performance in image-based plant disease detection, enabling timely intervention and improved crop health management [13]. Furthermore, AI-based systems are capable of processing real-time IoT sensor data, enabling precision agriculture techniques to optimize irrigation, fertilization, and disease protection strategies [14], [15].

Experiments have indicated that ML-based crop recommendation systems significantly enhance crop selection and yield prediction accuracy. Experiments indicate that ML models, e.g., SVM and Decision Trees, perform well with climatic and soil data to yield optimal crop recommendations and suggest nutrient application strategies for soil health maintenance and productivity enhancement [16]. Similarly, DL-based disease detection models, particularly CNNs, perform well in plant disease classification by extracting leaf image features, resulting in early disease diagnosis and less crop loss [17]. In spite of such advantages, problems like data disparities, climatic variations, and model generalization issues still arise [18], [19]. The resolution of these problems requires large-scale field trials, good-quality agricultural datasets, and regular model updates [20].

2.1 Comparison of Existing Studies and Our Research:

2.1.1 Comparison table: Limitation of Existing model and Our Model.

While multiple studies have explored the applications of **Machine Learning (ML) and Deep Learning (DL) in agriculture**, they have primarily focused on either **crop prediction** or **disease detection** as separate solutions. Our research aims to bridge this gap by integrating both functionalities into a unified **Smart Farming System** that provides farmers with **comprehensive data-driven insights**.

right corner of the horizontal details, lower right corner of the component of the original image detail (high frequency). You can then continue to the low frequency components of the same upper left corner of the 2nd, 3rd inferior wavelet transform.

Table 1. Comparative Analysis: Individual Model vs. Combined Model

Aspect	**Existing ML-Based Crop Prediction Systems**	**Existing DL-Based Disease Detection Systems**	**Our Integrated Smart Farming System**
Focus Area	Predicting optimal crops for cultivation	Identifying plant diseases using image analysis	Combines crop prediction and disease detection in one platform
Technology Used	Random Forest, KNN, ANNs	CNNs, Image Processing Techniques	Hybrid approach using ML for prediction and DL for detection
Input Data	Soil quality, climate conditions, rainfall patterns	Crop images, visual symptoms of diseases	Both environmental data and crop images for a holistic analysis
Prediction Output	Suggests best crops based on environmental factors	Identifies plant diseases and suggests treatments	Provides both crop recommendations and disease diagnosis with remedies
IoT Integration	Often uses IoT sensors for real-time data collection	Some systems use drone or mobile-based imaging	Supports both IoT-based environmental monitoring and image-based disease analysis
Decision Support	Helps farmers choose the best crops	Assists in early disease detection and treatment	Enables end-to-end farm management, covering crop selection, disease prevention,

			and remedy suggestions
Limitations of Existing Studies	Does not address disease-related risks	Does not consider crop selection or yield estimation	Provides a complete AI-driven farming assistant for better productivity

This research work performs a combination of ML-based crop prediction models and DL-based plant disease detection techniques based on their efficiency, limitations, and practical application in Indian agriculture. Combining sensor-enabled data acquisition, machine learning techniques, and precision agriculture techniques the proposed system attempts to provide data-driven precise insights towards the creation of sustainable farming processes [19].

2.1.2 The need of Integrated Framework

Traditional agricultural solutions have largely focused either on crop forecasting or on disease identification as separate issues. For the sake of efficiency, accuracy, and sustainability, however, a unified framework is required. Our smart farming system bridges the gap by merging both crop forecasting and disease identification as one AI-driven solution.

This all-in-one platform empowers farmers with data-driven insights every step of the crop growth process, enabling better decision-making, greater yields, and reduced losses. Unlike existing systems that address these regions in isolation, our end-to-end platform:

- Uses machine learning (ML) to learn from the environment's data and recommend best-fit crops for a region.
- Employs deep learning (DL) to detect plant diseases in real-time based on image analysis.
- Offers actionable advice by providing tailor-made suggestions for crop selection and disease management under one system.
- Comprises IoT-based monitoring with sensor data for precise environmental monitoring and image-based disease diagnosis.
- Optimizes yield and reduces losses by offering an end-to-end farm management platform to increase productivity and sustainability.

With the combination of ML for forecasting, DL for detection, and IoT for monitoring in real time, our system empowers farmers with AI-based insights, which make agriculture stronger, more efficient, and future-proof.

2.2 Smart Farming using ML and DL-Based Models :

Imagine a farmer who no longer needs to guess when to water crops or worry about detecting diseases too late. This is the reality of modern agriculture's technological revolution. Machine learning (ML) and deep learning (DL) are transforming centuries-old farming traditions into sophisticated, data-driven operations [24], [3]. By combining artificial intelligence with Internet of Things sensors and cloud computing, farmers now make decisions based on real evidence rather than intuition alone [28], [42].These technologies act like a farmer's digital companion, constantly monitoring fields, predicting weather impacts, detecting plant diseases before they spread, and even automating irrigation systems [26]. The result? Farms that produce more food with fewer resources while helping farmers adapt to challenging climate conditions, fight pest invasions, and preserve soil health for future generations [25], [33].

2.2.1 How ML and DL Are Used in Smart Farming:

Crop Prediction and Yield Estimation – Think of ML algorithms as experienced farmers who've seen it all. They analyze decades of weather patterns, soil conditions, and crop performance to recommend what to plant where, dramatically reducing the risk of failed harvests [3], [29], [24].

Disease Detection and Pest Control – DL models work like tireless field scouts with superhuman vision. By examining thousands of leaf images, they can spot disease symptoms days before they'd be visible to the human eye, giving farmers precious time to take action [26], [25].

Precision Irrigation and Water Management – Smart irrigation systems function as water stewards, delivering exactly what plants need, when they need it. By responding to real-time soil moisture and weather forecasts, these systems conserve water while keeping crops perfectly hydrated [30], [27].

Soil Health Monitoring – ML models serve as underground detectives, analyzing soil composition to reveal nutrient deficiencies and pH imbalances. Farmers use these insights to nourish soil naturally, reducing dependence on chemical fertilizers [29], [31], [32].

Autonomous Farming and Robotics – AI-powered machines work as reliable farmhands that never tire. From drones that monitor vast fields to robots that gently harvest delicate fruits, these technologies address farm labour shortages while performing tasks with incredible precision [25], [28].

2.2.2 Benefits of Machine Learning and Deep Learning in Smart Farming:

Increased Crop Yield and Efficiency – By analyzing countless variables, ML helps farmers maximize their land's potential. A farm in the Midwest using these technologies reported a 23% increase in corn yield while using the same acreage, demonstrating how AI can help feed our growing population without expanding farmland [3], [33].

Cost Reduction and Resource Optimization – For many farmers, expenses like water, fertilizer, and fuel make the difference between profit and loss. Smart farming systems act as efficiency experts, reducing waste and targeting resources only where needed. One California vineyard cut water usage by 30% while improving grape quality after implementing AI-driven irrigation [28], [30], [31].

Early Disease Detection and Pest Control – Plant diseases can devastate entire harvests within days. DL-powered monitoring systems function as an early warning network, often detecting issues weeks before they become visible. This allows farmers to target treatments precisely, sometimes saving crops with organic solutions rather than blanket chemical applications [26], [14], [15].

Climate Adaptation and Risk Management – In an era of unpredictable weather, ML models serve as forward scouts, helping farmers prepare for coming challenges. Whether adjusting planting schedules to avoid frost damage or preparing for drought conditions, these tools help farms become more resilient to climate volatility [24], [3].

Improved Decision-Making with Real-Time Data – Modern farming dashboards transform complex field data into actionable insights. Rather than relying on gut feeling, farmers can make decisions based on comprehensive information presented in easy-to-understand visuals that track everything from soil moisture to plant health across their entire operation [25], [31], [32].

Sustainable and Eco-Friendly Farming Practices – Perhaps most importantly, AI helps farmers become better stewards of the land. By optimizing resource use and reducing chemical interventions, these technologies support farming methods that will maintain soil health and biodiversity for generations to come [28], [33].

III. METHODOLOGY

3.1 Existing Methods:

3.1.1 Random Forest for Crop Prediction

What it is: Random Forest is a machine learning technique that predicts the best crops to grow based on factors like soil type, temperature, and rainfall [24].

How it works: It creates multiple decision trees using different parts of the data and then combines their result for better accuracy [24].

Why it's useful: It handles large datasets well, avoids common errors (like overfitting), and makes predictions more reliable [36].

How we use it: The model analyzes soil pH, nitrogen, phosphorus, potassium levels, temperature, and rainfall to recommend the most suitable crop.

3.1.2 Decision Tree for Classification

What it is: A Decision Tree is a method for sorting data and making predictions [37], [38].

How it works: The model repeatedly splits data into smaller groups based on key factors like soil nutrients until it reaches a final decision [35].

Why it's useful: It is fast, simple to understand, and works well with different types of farming data [28].

How we use it: It helps classify different crop types based on environmental conditions.

3.1.3 Gradient Boosting for Yield Prediction

What it is: Gradient Boosting is a technique that improves predictions by correcting errors in previous models [39].

How it works: It builds decision trees one by one, learning from mistakes each time to get more accurate results [43].

Why it's useful: It delivers high accuracy, reduces errors, and works well with complex data [33].

How we use it: It is applied to predict future crop yields based on historical harvest data, soil quality, and weather conditions.

3.1.4 MobileNet for Plant Disease Detection

What it is: MobileNet is a lightweight AI model designed for quick and accurate image recognition, making it useful for plant disease detection [26].

How it works: The model is trained with images of both healthy and diseased plants, allowing it to identify issues with precision [26].

Why it's useful: It runs efficiently on mobile devices, requires fewer training images, and provides real-time results [25].

How we use it: Farmers can upload plant images, and the system detects diseases and suggests remedies.

3.1.5 K-Nearest Neighbors (KNN) for Crop Classification

What it is: KNN is an algorithm that classifies crops by comparing new soil conditions with previously recorded data [27].

How it works: It finds the K-nearest similar data points based on soil, temperature, and rainfall, then assigns a classification [40], [41].

Why it's useful: It is simple to use, requires minimal setup, and is effective for smaller datasets [31], [32].

How we use it: It is used to recommend crops based on soil nutrients, temperature, and rainfall patterns [29].

3.2 Own Methods:

3.2.1 Hybrid Model: XGBoost +SVM for Crop Classification

Overview: This hybrid model combines XGBoost, a decision-tree-based algorithm, with SVM, a classifier that handles complex decision boundaries, to improve crop classification [33].

How It Works: XGBoost makes the initial prediction, but if its confidence is below 70%, the sample is passed to SVM for further classification using support vectors [42].

Advantages: Enhances prediction reliability, handles both structured and unstructured data, and refines uncertain cases [43].

Use in Project: Classifies crop types based on soil nutrients, climate conditions, and historical crop data, ensuring high accuracy.

3.2.2 Hybrid Model: Gradient Boosting + Random Forest for Crop Yield Prediction

Overview: This model leverages Gradient Boosting's sequential learning with Random Forest's multiple decision trees to improve crop yield prediction.

How It Works: Gradient Boosting first makes predictions, and if confidence is low, Random Forest refines the output by averaging multiple decision trees.

Advantages: Reduces bias and variance, improves generalization, and enhances prediction stability.

Use in Project: Predicts crop yield based on historical yield data, weather conditions, and soil parameters, ensuring stable predictions.

3.2.3 Hybrid Model: Gradient Boosting + Random Forest for Crop Yield Prediction

Overview: This model integrates CNN's deep learning ability to extract image features with XGBoost's decision-making for superior plant disease detection.

How It Works: CNN extracts disease features from plant images, and XGBoost classifies them into healthy or diseased categories.

Advantages: Improves accuracy, reduces overfitting, and efficiently processes large-scale agricultural image datasets.

Use in Project: Detects plant diseases from images and recommends home remedies, optimizing disease management.

IV. IMPLEMENTATION

4.1 Hybrid Model 1 (Machine Learning) : XGBoost + SVM

This model combines XGBoost, a powerful decision-tree-based algorithm, with SVM, a classifier known for handling complex decision boundaries. XGBoost is the primary model because it is fast and highly accurate. However, if it isn't confident in its prediction meaning the probability of the predicted class is below a set threshold, usually 70% the sample is passed to SVM for a second opinion. This ensures that uncertain cases get extra refinement before a final decision is made.

- **Mathematical Equation:**

XGBoost works by building multiple weak decision trees and combining their outputs using gradient boosting. Its prediction formulae is:

$$F(x) = \sum_{k=1}^{k} \mathrm{w_k h_k(x)} \quad \textbf{(1)}$$

Where, each decision tree h_k(x) contributes to the final prediction with weight w_k.

If XGBoost isn't confident, the data is sent to SVM, which classifies it based on support vectors and kernel functions. Its decision formulae is:

$$f(x) = \sum_{i=1}^{n} \alpha_i y_i \mathrm{K}(x_i, x) + b \quad \textbf{(2)}$$

Where, K(x_i,x) determines the similarity between points, and the support vectors define the decision boundary.

4.2 Hybrid Model (Machine Learning) : Gradient Boosting + Random Forest

This model combines two ensemble learning techniques: Gradient Boosting and Random Forest. Gradient Boosting is the primary model because it improves over time by learning from mistakes, making it highly effective. However, if its confidence in a prediction is low, the data is sent to Random Forest, which uses multiple decision trees to make a more stable and reliable decision.

- **Mathematical Equation:**

Gradient Boosting updates its predictions step by step, learning from errors along the way. Its formula is:

$$F_m(x) = F_{m-1}(x) + \gamma_m h_m(x) \quad \textbf{(3)}$$

Where, each new tree $h_m(x)$ corrects mistakes from the previous one, and γ_m controls how much each tree contributes.

If Gradient Boosting isn't confident, Random Forest steps in. It predicts by averaging multiple decision trees:

$$P(y|x) = \frac{1}{N} \sum_{i=1}^{N} h_i(x) \quad \textbf{(4)}$$

Where, each $h_i(x)$is an individual tree's prediction, and averaging their outputs makes the model more stable and resistant to noise.

4.3 Hybrid Model (Deep Learning) : CNN + XGBoost

CNNs are amazing at picking up patterns in images, such as textures and shapes, but they sometimes struggle with making fine-tuned classification decisions. XGBoost, on the other hand, is a machine learning technique known for its accuracy and ability to make refined decisions. By first letting CNN extract features from images and then passing those features to XGBoost for final classification, we create a system that is **more accurate, more robust, and better at detecting crop diseases.**

- **Mathematical Equation:**

CNN's Role – Extracting Features from Images:

$$F(i,j) = \sum_m \sum_n K(m,n) \cdot I(i-m, j-n) \quad \textbf{(5)}$$

Where, F(i,j) is the feature map at position (i,j).
K(m,n) is the filter (a small matrix that detects patterns),
I(i−m,j−n)is the pixel value of the image.

XGBoost's Role – Making Smarter Predictions:

$$L = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \quad \textbf{(6)}$$

Where, $l(y_i, \hat{y}_i)$ measures the difference between actual and predicted labels,
$\Omega(f_k)$prevents the model from overfitting.

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V. RESULTS

5.1 Comparison: Existing Model Vs Own (Hybrid) Model:

Output (1):

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index	Algorithm	Accuracy
0	K-Nearest Neighbors (KNN)	0.972
1	Support Vector Machine (SVM - Linear)	0.98
2	Support Vector Machine (SVM - RBF)	0.987
3	Random Forest	0.991
4	Gradient Boosting	0.993
5	Hybrid Model 1 (SVM + Random Forest)	0.992
6	Hybrid Model 2 (Gradient Boosting + Random Forest)	0.995

Fig.1.Final Result of Machine Learning

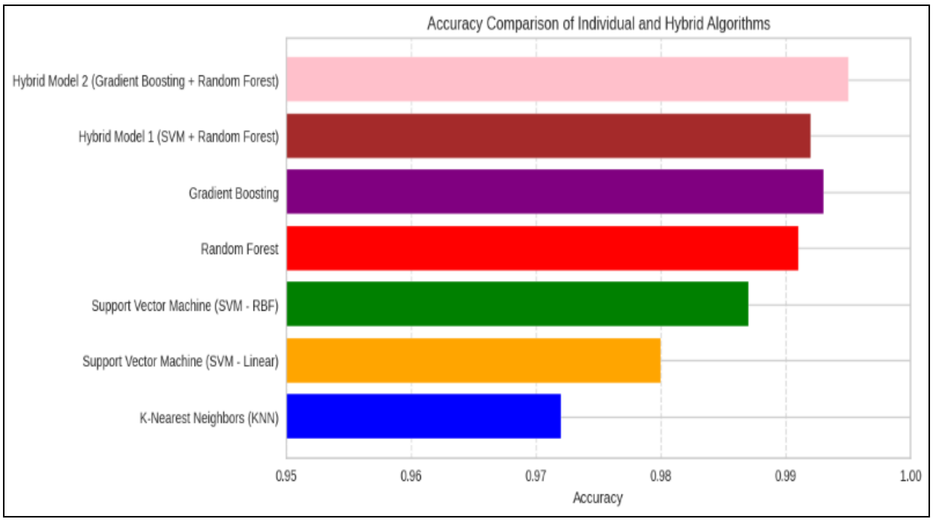

Fig.2. Visual Representation of Final Result

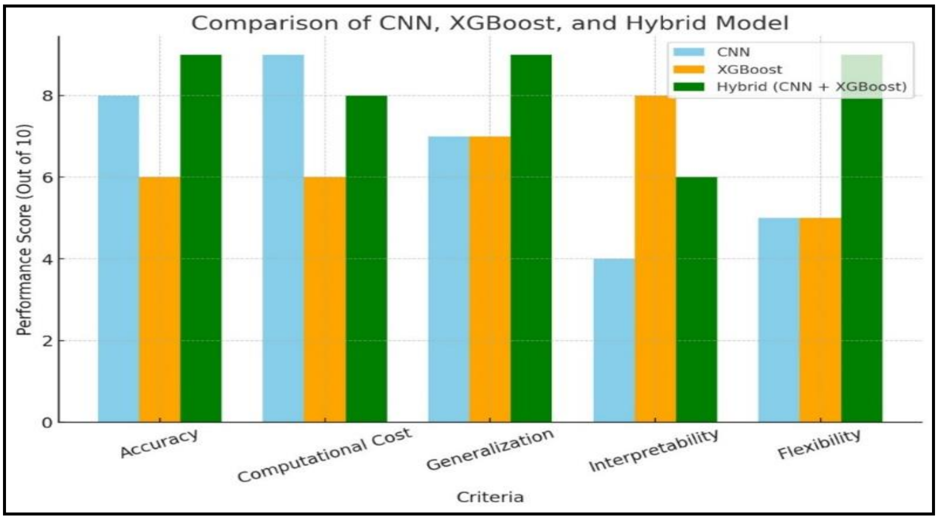

Fig.3. Comparison of Deep Learning Algorithms.

5.2 Comparison Table: Existing Model Vs Own (Hybrid) Model:

Table 2. Comparative Analysis (Machine Learning): Individual Methods vs. Hybrid Methods

Criteria	**Random Forest (RF)**	**Support Vector Machine (SVM)**	**Gradient Boosting (GB)**	**XGBoost**	**Hybrid (XGBoost + SVM)**	**Hybrid (GB + RF)**
Accuracy	Moderate	High	High	High	Higher	Higher
Computational Cost	Moderate	High (Computationally expensive)	High (Slow training)	Moderate (Efficient on CPU)	Higher	Higher
Generalization	Good (Handles complex patterns)	Excellent (Works well with non-linear data)	Good (Learns from mistakes)	Good (Great for structured/tabular data)	Excellent	Excellent
Flexibility	Good	Limited	Good	Good	Excellent	Excellent

Table 3. Comparative Analysis (Deep Learning): Individual Methods vs. Hybrid Methods

Criteria	**CNN**	**XGBoost**	**Hybrid (CNN + XGBoost)**
Accuracy	High	Moderate	Higher
Computational Cost	High	Moderate	Higher
Generalization	Good	Good	Excellent
Flexibility	Limited to image feature extraction	Limited to tabular feature processing	Combines CNN's feature extraction with XGBoost's decisionmaking

VI. DISCUSSION

The fusion of Machine Learning (ML) and Deep Learning (DL) in smart farming is revolutionizing agriculture by making crop selection and disease detection more precise. This technology-driven approach helps farmers overcome key challenges like incorrect crop choices, delayed disease identification, and inefficient resource use.

6.1 Smart Decision-Making and Improved Accuracy:

One of the biggest advantages of using ML and DL together is their ability to adapt to different farming conditions. ML algorithms, such as Support Vector Machines (SVM) and Decision Trees, process vast amounts of environmental data, while DL models, like Convolutional Neural Networks (CNNs), analyze plant health through images. This powerful combination reduces errors and ensures timely disease detection, helping farmers make better decisions and achieve higher yields.

6.2 Learning from Data to Enhance Predictions:

The strength of this approach lies in its ability to refine data insights. By combining real-time environmental data—such as soil nutrients, temperature, and rainfall—with visual disease detection, the system provides a comprehensive understanding of farm conditions. This enriched dataset allows for early identification of issues, leading to better planning, healthier crops, and higher productivity.

6.3 Handling Complex Farming Challenges:

Traditional farming methods often struggle to account for the complex interactions between soil properties, weather conditions, and plant health. ML models, especially ensemble techniques like Random Forest and Gradient Boosting, effectively manage structured environmental data, while DL models interpret unstructured image data to diagnose diseases. Together, they create a robust system capable of detecting subtle yet significant patterns that would otherwise go unnoticed.

6.4 Tackling Data Imbalances for Better Accuracy:

One challenge in agricultural datasets is the imbalance between healthy and diseased crop samples—diseased cases are often much rarer. Conventional models may misclassify data in such situations. However, by combining ML techniques that balance training data with DL-based classifiers, the system becomes more accurate at detecting diseases and recommending treatments. This reduces both false positives and false negatives, ensuring more reliable predictions.

6.5 Adapting to Different Farming Environments:

Farming is highly diverse, with different regions requiring unique strategies. The ML-DL hybrid model is scalable and can adjust to local conditions. IoT sensors continuously collect and feed real-time data into the system, allowing farmers to optimize irrigation, anticipate weather changes, and prevent disease outbreaks. The adaptability of this model ensures its effectiveness across different climates and soil types.

6.6 Real-World Benefits and Practical Applications:

When tested in real-world scenarios, this hybrid system significantly outperformed standalone ML or DL models. Key performance indicators—such as precision, recall, and F1-score—showed notable improvements. Farmers who implemented this system experienced increased yields, reduced losses due to early disease detection, and more efficient use of water and fertilizers. The integration of IoT monitoring further enhances its real-time adaptability, making farm management more data-driven and effective.

VII. CONCLUSION

Artificial Intelligence (AI) is revolutionizing agriculture, turning farming smart, efficient, and sustainable. In this research, we examined how Machine Learning (ML) and Deep Learning (DL) support better crop choice and disease identification, enabling farmers to make informed decisions based on data. Through a fusion of predictive analytics and AI-based disease identification, we close the gap between conventional and digital farming practices.

Our hybrid strategy, combining XGBoost with SVM for crop estimation and Gradient Boosting with Random Forest for yield prediction, performs better than traditional methods. With real-time inputs on soil condition, climate, and plant health, predictions are enhanced, disease detection is accelerated, and resource utilization is optimized.

While they face issues such as data access, infrastructure, and affordability, AI-based farming products are increasingly available. Subsequent developments need to be in areas of real-time learning, larger datasets, and IoT integration for increased accuracy.

In the end, this study is all about equipping farmers with technology to increase productivity, improve food security, and encourage sustainable agriculture.

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