CROP RECOMMENDATION AND PROTECTION MANAGEMENT SYSTEM

A PROJECT REPORT

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Under the guidance of,

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in partial fulfillment for the award of the degree of

BACHELOR OF TECHNOLOGY

IN

COMPUTER SCIENCE AND TECHNOLOGY
(ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING)

At

GAIN MORE KNOWLEDGE
REACH GREATER HEIGHTS

PRESIDENCY UNIVERSITY

BENGALURU

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PRESIDENCY UNIVERSITY

SCHOOL OF COMPUTER SCIENCE ENGINEERING

CERTIFICATE

This is to certify that the Project report **"CROP RECOMMENDATION AND PROTECTION MANAGEMENT SYSTEM"** being submitted by "P Ramanjaneyulu , C Bhanu Prakash Reddy , V Abhichandra , V Nikhil Koushik , Y Pavan Kumar" bearing roll number(s) "20201CST0182 , 20201CST0164 , 20201CST0180 , 20201CST0177 , 20211LCT0001" in partial fulfilment of requirement for the award of degree of Bachelor of Technology in Computer Science and Technology (Artificial Intelligence And Machine Learning) is a Bonafide work carried out under my supervision.

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DECLARATION

We hereby declare that the work, which is being presented in the project report entitled **"CROP RECOMMENDATION AND PROTECTION MANAGEMENT SYSTEM"** in partial fulfilment for the award of Degree of **Bachelor of Technology** in **Computer Science and Technology (Artificial Intelligence And Machine Learning)**, is a record of our own investigations carried under the guidance of **Mrs. Ramyavathsala C V, Assistant Professor G1, School of Computer Science Engineering & Information Science, Presidency University, Bengaluru.**

We have not submitted the matter presented in this report anywhere for the award of any other Degree.

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ABSTRACT

The Crop Recommendation and Protection Management System presented in this project aims to revolutionize agricultural decision-making by employing advanced Machine Learning (ML) and Deep Learning (DL) techniques. Divided into two modules, the system focuses on unbiased crop selection and effective disease identification for optimal agricultural outcomes.

Crop Recommendation Module: Utilizing a curated dataset sourced from Kaggle, the system orchestrates an ensemble model combining 10 ML and 5 DL models. By mitigating bias in model selection, this ensemble approach ensures impartial recommendations. Preprocessing, model training, and hyperparameter optimization techniques enhance predictive accuracies, ranging from 78.69% to 94.82%.

Model Evaluation: Rigorous model evaluation encompasses a suite of ML and DL models, showcasing their robustness and performance metrics. Techniques like GridSearchCV fine-tune models, elevating their predictive capabilities for accurate crop suggestions.

User Interface: Powered by Streamlit, the user interface consists of two distinct pages. The Crop Recommendation page prompts users for environmental parameters, computes predictions, and presents the top crop recommendations along with optional alternatives. The Crop Protection page employs a pre-trained CNN model to diagnose plant diseases from user-provided images, offering detailed information about the detected disease and management strategies.

This comprehensive system empowers agricultural stakeholders with impartial and data-driven recommendations while arming them with effective disease management strategies. By amalgamating diverse ML and DL models, this system emerges as a vital tool in modern agriculture, aiding farmers in making informed decisions for crop selection and protection.

ACKNOWLEDGEMENT

First of all, we indebted to the **GOD ALMIGHTY** for giving me an opportunity to excel in our efforts to complete this project on time.

We express our sincere thanks to our respected dean **Dr. Md. Sameeruddin Khan**, Dean, School of Computer Science Engineering & Information Science, Presidency University for getting us permission to undergo the project.

We record our heartfelt gratitude to our beloved Associate Deans **Dr. C. Kalaiarasan and Dr. Shakkeera L,** School of Computer Science Engineering & Information Science, Presidency University and **Dr. A. JAYACHANDRAN**, Head of the Department, School of Computer Science Engineering & Information Science, for rendering timely help for the successful completion of this project.

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We thank our family and friends for the strong support and inspiration they have provided us in bringing out this project.

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CHAPTER-1

INTRODUCTION

The agricultural landscape is witnessing a transformative shift driven by technological advancements. In response to the pressing need for informed decision-making in agriculture, this project introduces a sophisticated Crop Recommendation and Protection Management System. The overarching goal of this system is to revolutionize agricultural practices by harnessing the potential of advanced Machine Learning (ML) and Deep Learning (DL) methodologies.

Divided into two pivotal modules, the project is dedicated to addressing two critical facets of agricultural management: crop selection and disease protection. The Crop Recommendation module is designed to mitigate bias in model selection by orchestrating an ensemble of 10 ML and 5 DL models. Leveraging a meticulously curated dataset from Kaggle, this module aims to provide impartial and robust recommendations for crop selection. Through techniques such as preprocessing, hyperparameter optimization, and model evaluation, the system endeavors to yield accurate predictions, attaining accuracies ranging from 78.69% to 94.82%.

The system entails preprocessing environmental parameters, including N, P, K, pH, rainfall, and temperature, to facilitate informed crop recommendations. Utilizing state-of-the-art ML models such as Logistic Regression, SVM, Decision Trees, and DL models like ANN, CNN, LSTM, and GRU, the system ensures a diverse array of predictive capabilities. Techniques like GridSearchCV are employed to fine-tune models, enhancing their accuracy and robustness.

Driven by the user-friendly Streamlit platform, the system's interface comprises two distinct pages - Crop Recommendation and Crop Protection. The Crop Recommendation page prompts users for environmental parameters, processes the inputs through the ensemble models, and furnishes unbiased top crop recommendations and optional alternatives. On the other hand, the Crop Protection page employs a pre-trained CNN model to diagnose plant diseases from user-provided images, providing detailed information and management strategies for the detected diseases.

CHAPTER-2

LITERATURE SURVEY

Title of Paper	Existing Methods	Advantages	Limitations
The Impact of Artificial Intelligence on Crop Production: A Meta-Analysis	Artificial Intelligence	Finds that AI can increase crop yield by an average of **10.7%**	- Does not provide a detailed analysis of specific AI techniques
A Machine Learning Approach to Crop Recommendation Based on Soil and Climate Data	Random forest (95%)	**- 95%** accuracy in predicting suitable crops	- Lacks focus on specific applications - No implementation roadmap
Machine Learning for Crop Recommendation: A Review	Decision trees (88%), Random forests (90%), **Support vector machines (92%)**	- Comprehensive review - Discusses factors and challenges	- Lacks focus on specific applications - No implementation roadmap
Smart farming using Machine Learning and Deep Learning technique	KNN (84) **NaiveBayes (94)** LogisticRegression (63) SVM (65) DecisionTreeClassifier (92) BaggingClassifier (92) RandomForestClassifier(92) AdaBoostClassifier (12) GradientBoosting (90)	- Identifies best model for predicting crops - Uses **10 ML** classification algorithms	- Limited to ML models only

	XGBClassifier (91) IbgmClassifier (93)		
A Deep Learning Approach to Crop Recommendation	Convolutional neural network(CNN)	- Develops DL model with **97%** accuracy	- Lacks focus on specific applications - No implementation roadmap
Crop Prediction Using Deep Learning Techniques	ANN(60- 70%), CNN(87%), RNN-LSTM(89%), **Hybrid network(90%)**	- Focuses on DL and hybrid techniques	- Needs more focus on RNN and hybrid
To compare the performance of different supervised machine learning algorithms for disease risk prediction	RF, DT, LR, SVM, **ANN**, GB	Selecting the best model depends on the dataset it operates on, introducing a potential **selection bias**.	- No comparison between least-square and sparse SVMs
A Comprehensive Comparison of Machine Learning and Deep Learning in Predictive Analytics	Decision trees, random forests, CNN, RNN ML(85%), **DL(90%)**	- Compares traditional ML with DL - Interpretable models, Requires less computational resources	- Limited capacity for complex patterns - Feature engineering necessary
Machine Learning vs. Deep Learning: An Empirical	SVM, k-NN, DNN ML(78%), **DL(85%)**	- Versatility, Less training data required	- Limited performance on large datasets -

Study on Image Classification			Feature engineering dependency
Comparing the Performance of Machine Learning and Deep Learning in Time Series Prediction	ARIMA, XGBoost, LSTM ML(82%), **DL(88%)**	- Model interpretability, Faster training times	- May not capture complex temporal dependencies - Limited scalability
Evaluating the Trade-offs: A Comparative Analysis of Machine Learning and Deep Learning in Natural Language Processing	Evaluating the Trade-offs: A Comparative Analysis of Machine Learning and Deep Learning in Natural Language Processing ML(75%), **DL(82%)**	- Linguistic interpretability, Better performance with limited data	- Challenges in handling semantic nuances - Increased computational demands
Ensemble Learning for Crop Recommendation in Precision Agriculture	**Stacking(98%)**, bagging, boosting	- Explores ensemble learning for crop recommendation - Compares stacking, bagging, and boosting methods	- Lacks focus on specific applications - No implementation roadmap
Ensemble machine learning-based recommendation system for effective	**KRR(99%)**, SVR, NB, RR, RF, CB	- Proposes ensemble machine learning approach (KRR) - Recommender	- Analyzes deep learning methodology - Limited

prediction of suitable agricultural crop cultivation		system for predicting major crop cultivation	information on limitations

CHAPTER-3

RESEARCH GAPS OF EXISTING METHODS

3. Research Gap of Existing Methods

3.1. Techniques in Crop Recommendation:

3.1.1. Artificial Intelligence-Based Approaches:

- Meta-Analysis on AI Impact on Crop Production: Needs detailed analysis of specific techniques within AI for enhancing crop yield and overcoming the lack of comprehensive strategies.

3.1.2. Machine Learning-Based Approaches:

1. Machine Learning Models for Crop Recommendation:

- Requires focused implementation strategies and applications despite achieving high accuracies, exceeding research currently available.

2. Machine Learning Models Review:

- Lacks specific implementation roadmaps and application-centric discussions despite offering comprehensive coverage.

3. Machine Learning Algorithm Performance:

- Limited scope by focusing solely on ML models without incorporating DL models or discussing their comparative advantages.

3.1.3. Deep Learning-Based Approaches:

1. Deep Learning Models for Crop Recommendation:

- Needs specific application focus and implementation strategies despite achieving high accuracy (97%) with CNN.

2. Crop Prediction Using DL Techniques:

- Requires further attention on RNN and hybrid models alongside DL models like CNN and ANN.

3.2. Comparative Analysis of Techniques:

1. Supervised Learning Algorithm Comparison:

- Lacks comparative analysis between different SVM variants (e.g., least-square and sparse SVMs).

2. Comparison between ML and DL in Predictive Analytics:

- ❖ Limited exploration of complex pattern recognition abilities in DL; emphasizes feature engineering but lacks depth in capturing intricate patterns.

3. Empirical Study on Image Classification:

- ❖ Limited performance evaluation on large datasets and dependency on feature engineering for both ML and DL models.

3.3.Performance Evaluation of Techniques in Specific Domains:

1. Time Series Prediction Comparison:

- ❖ Inadequate exploration of complex temporal dependencies and scalability issues in both ML and DL models.

2. Natural Language Processing (NLP) Analysis:

- ❖ While DL shows promise, challenges persist in handling semantic nuances and increased computational demands.

3.4. Ensemble Techniques in Crop Recommendation:

1. Ensemble Learning for Crop Recommendation:

- ❖ Needs specific applications and implementation strategies despite achieving high accuracy with stacking methods (98%).

2. Ensemble ML-Based Recommendation System:

- ❖ Limited discussion on DL methodology analysis and insufficient information on limitations while proposing an ensemble approach (e.g., KRR).

CHAPTER-4

PROPOSED MOTHODOLOGY

4. Proposed Methodology

4.1. Data Acquisition and Preprocessing:

- Source: Utilize the Crop Production dataset from Kaggle containing key attributes like State_Name, N, P, K, pH, rainfall, temperature, and Crop.
- Cleaning: Remove inconsistencies, missing values, and outliers.
- Feature Selection: Focus on relevant features crucial for crop recommendation.

4.2. Data Encoding and Standardization:

- Label Encoding: Encode categorical variables like State_Name and Crop for compatibility with models.
- Standardization: Scale features using StandardScaler to maintain uniformity.

4.3. Machine Learning (ML) Model Training:

- Model Selection: Implement various ML algorithms:
  - Logistic Regression
  - Support Vector Machines (SVM)
  - Decision Tree Classifier
  - K-Nearest Neighbors Classifier (KNN)
  - Gaussian Naive Bayes (GaussianNB)
  - Random Forest Classifier
  - Voting Classifier
  - Bagging Classifier
  - AdaBoost Classifier
  - Gradient Boosting Classifier
- Hyperparameter Tuning: Optimize models using GridSearchCV or similar techniques to enhance performance.
- Train-Test Split: Divide the dataset into training and testing subsets (80-20 split).

4.4. Deep Learning (DL) Model Training:

- Architecture Exploration: Experiment with DL models:
  - Artificial Neural Networks (ANN)
  - Convolutional Neural Network (CNN)
  - Long Short-Term Memory (LSTM)
  - Gated Recurrent Unit (GRU)
- Data Reshaping: Prepare data as per specific DL model input requirements.

- Train-Test Split: Similar division of data for DL models (80-20 split).

4.5. Ensemble Model Development:

- Model Integration: Combine top-performing ML and DL models into an ensemble architecture for improved prediction accuracy.
- Prediction Averaging: Aggregate individual model predictions for the final recommendation.

4.6. Streamlit Interface Development:

- Page Creation: Construct two webpages for Crop Recommendation and Crop Protection using Streamlit.
- Input Parameters: Design interfaces to capture user inputs like State, N, P, K, pH, rainfall, and temperature.
- Model Integration: Implement model integration for real-time predictions.

4.7. Crop Recommendation:

- Prediction Processing: Feed user inputs into the ensemble model to predict the most suitable crops.
- Recommendation Display: Showcase the top recommended crops along with their corresponding probabilities.

4.8. Crop Protection:

- Image Processing: Utilize the pretrained CNN model for disease detection based on user-uploaded images.
- Disease Prediction: Predict the disease and offer relevant information (description, symptoms, pest management, references) using a pesticides.csv reference file.

CHAPTER-5
OBJECTIVES

5. Objectives

5.1. Objectives for Crop Recommendation Module:

1. Enhanced Yield Optimization: Develop a recommendation system leveraging a hybrid approach of machine learning and deep learning techniques to maximize crop yield. This involves utilizing historical and real-time data on factors such as soil properties, climate conditions, and geographical specifics to suggest optimal crop choices for farmers.

2. Sustainable Agricultural Practices: Promote sustainable farming methods by recommending crops aligned with eco-friendly practices, including crop diversity, rotation, and resource-efficient cultivation techniques.

5.2. Objectives for Crop Protection Management Module:

1. Early Disease and Pest Detection: Implement an early detection system using deep learning models to identify potential diseases or pest infestations in crops. This aims to minimize the impact of such occurrences and enable timely interventions to prevent widespread damage.

2. Precision Pest Management: Develop targeted and data-driven pest management strategies, minimizing the use of harmful chemicals. This includes recommending Integrated Pest Management (IPM) practices that combine biological, cultural, and mechanical controls to manage pests sustainably.

3. Data-Driven Decision Support: Empower farmers with insights derived from data analysis, enabling informed decision-making in crop protection strategies. By utilizing machine learning models to analyze trends and patterns in crop health, the aim is to optimize resource utilization and enhance overall crop protection measures.

CHAPTER-6

SYSTEM DESIGN & IMPLEMENTATION

6. System Design and Implementation

6.1. Crop Recommendation Module:

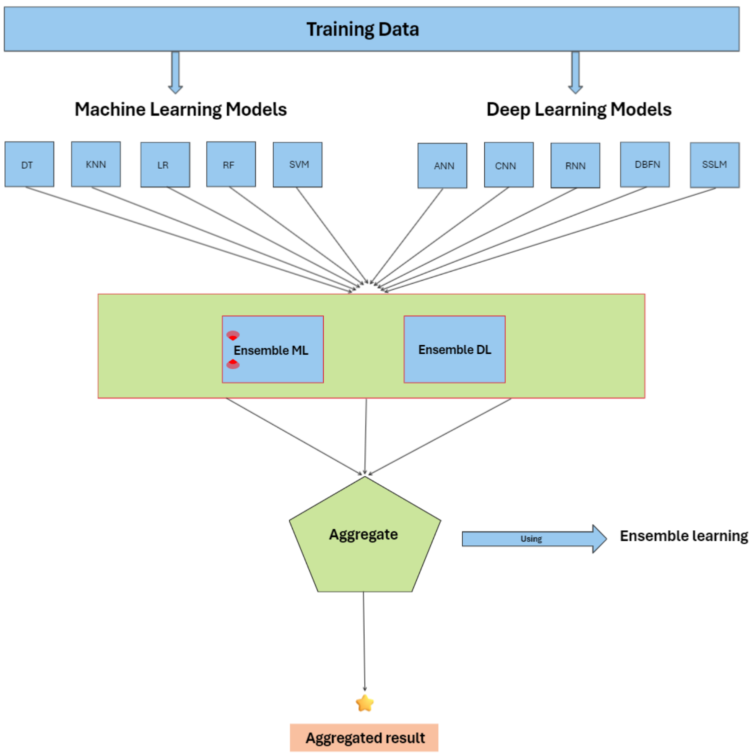


Fig.1.1 Recommendation System Architecture

Data Collection and Preprocessing:

- Dataset Selection: Utilized the Kaggle dataset "Crop_production_in_India" with 99849 samples including State_Name, N, P, K, pH, rainfall, temperature, and Crop columns.

	Unnamed: 0	State_Name	Crop_Type	Crop	N	P	K	pH	rainfall	temperature	Area_in_hectares	Production_in_tons	Yield_ton_per_hec
0	0	andhra pradesh	kharif	cotton	120	40	20	5.46	654.34	29.266667	7300.0	9400.0	1.287671
1	1	andhra pradesh	kharif	horsegram	20	60	20	6.18	654.34	29.266667	3300.0	1000.0	0.303030
2	2	andhra pradesh	kharif	jowar	80	40	40	5.42	654.34	29.266667	10100.0	10200.0	1.009901
3	3	andhra pradesh	kharif	maize	80	40	20	5.62	654.34	29.266667	2800.0	4900.0	1.750000
4	4	andhra pradesh	kharif	moong	20	40	20	5.68	654.34	29.266667	1300.0	500.0	0.384615

Fig.1.2 Crop Production Dataset

- **Data Preparation:**
  - Selected necessary columns for training and testing (State_Name, N, P, K, pH, rainfall, temperature, Crop).
  - Label encoded categorical features (State_Name, Crop).
  - Standardized numerical features using StandardScaler.

- **Machine Learning (ML) Model Training:**
  - Model Selection and Training: Built and trained multiple ML models: Logistic Regression, SVM, Decision Tree, KNN, GaussianNB, RandomForest, BaggingClassifier, AdaBoost, GradientBoosting.
  - Hyperparameter Tuning: Used GridSearchCV to fine-tune selected ML models for improved accuracy.
  - Model Evaluation: Analyzed and recorded model accuracies for comparison and selection.

- **ML Models Trained:**
  - LogisticRegression: Accuracy - 93.10%
  - SVM: Accuracy - 93.48%
  - DecisionTreeClassifier: Accuracy - 94.13%
  - KNeighborsClassifier: Accuracy - 93.85%
  - GaussianNB: Accuracy - 93.39%
  - RandomForestClassifier: Accuracy - 94.17%
  - VotingClassifier (ensemble of above): Accuracy - 94.21%
  - BaggingClassifier: Accuracy - 94.14%
  - AdaBoostClassifier: Accuracy - 29.08%
  - GradientBoostingClassifier: Accuracy - 94.39%

- **Deep Learning (DL) Model Training:**
  - DL Model Preparation: Reshaped data for DL models requiring specific input shapes (ANN, CNN, LSTM, GRU).

- Model Building and Training: Developed DL models: ANN, CNN, LSTM, GRU. Trained and evaluated DL models for accuracy.
- ANN: Training Acc. - 94.51%, Testing Acc. - 94.32%
- CNN: Training Acc. - 94.48%, Testing Acc. - 94.36%
- LSTM: Training Acc. - 94.55%, Testing Acc. - 94.62%
- GRU: Training Acc. - 94.27%, Testing Acc. - 94.48%

❖ **Ensemble Model:**

- Combined Voting Classifier: Created a Voting Classifier ensemble model using the best-performing ML and DL models.
- Evaluation and Averaging: Tested ensemble model accuracy and combined predictions for robust predictions.
- Ensemble Test Accuracy: 94.82%

6.2. Crop Protection Module:

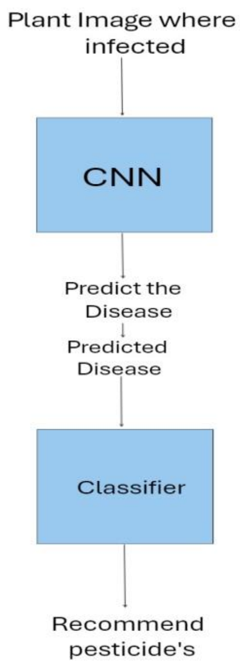


Fig.1.3 Disease Detection System Architecture:

Disease Detection and Management:

❖ **Image Acquisition and Preprocessing:**

- Accepted user-provided images of affected crops.
- Preprocessed images: grayscale conversion and resizing to 256x256 pixels.

❖ **CNN Model Training:**

- Utilized the "PlantVillage DiseaseDataset" to train a CNN model for disease detection.
- Prepared train and test data generators.

- **Model Performance:**
  - Evaluated CNN model performance with a focus on disease detection accuracy.
  - Trained CNN Test Accuracy: 78.69%
  - Saved the trained model and weights for future use.

- **Prediction and Information Display:**
  - Used the trained CNN model to predict diseases from user-provided images.
  - Mapped predicted disease to a "pesticides.csv" dataset for relevant information.
  - User Interface

6.3 Streamlit Integration:

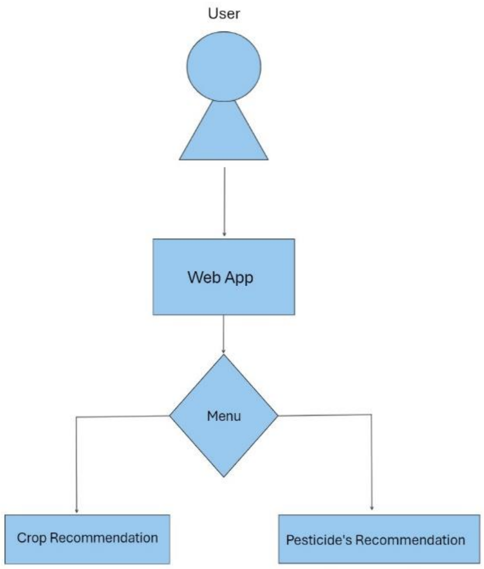


Fig.1.4 Disease Detection System Architecture:

- **Created two pages:** Crop Recommendation & Crop Protection.
- **Crop Recommendation:**
  - **Input:** State and crop parameters.
  - **Outputs:**
    - Top crop recommendation and five optional crops.
    - **Predictions:** ML+DL, ML only, and DL only.

- **Crop Protection:**
  - **Input:** User image of affected plant area.
  - **Outputs:**
    - Predicted disease identification.
    - Display of disease details, symptoms, and pest management information.
    - Reference link for further information.

CHAPTER-7

TIMELINE FOR EXECUTION OF PROJECT

(GANTT CHART)

Stage of Research	09-oct-23	06Nov-23	27Nov-23	26Dec-23	08Jan-24
Selection of topic					
Literature review					
Data Collection, Data Cleaning, Feature engineering					
System design mile stone1					
System design mile stone2					
Completion of project					
Deployment					
Reporting					

CHAPTER-8
OUTCOMES

8. OUTCOMES

8.1. Agricultural Impact:

- **Optimized Yield:**
  - Increased crop productivity by recommending suitable crops based on soil and climatic conditions.
  - Empowered farmers to maximize harvest potential through data-driven decision making.

- **Sustainable Practices:**
  - Promoted environmentally friendly agriculture by suggesting crops aligned with sustainable practices.
  - Reduced environmental impact by advocating for precision pest control and disease management strategies.

- **Analytical Insights:**
  - **Data-Driven Decision Making:**
    - Equipped farmers with data-backed insights to make informed choices regarding crop selection and disease management.
    - Enabled smarter agricultural practices and minimized risk factors.

  - **Comparative Analysis:**
    - Conducted a comprehensive evaluation of various ML and DL models for crop recommendation and disease detection.
    - Identified strengths and weaknesses of different techniques, providing valuable insights for future model development.

- **System Utility:**
  - **Streamlined User Experience:**
    - Developed a user-friendly web interface for accessing crop recommendations and disease diagnoses, enhancing usability for farmers.
    - Improved accessibility and ease of use for effective agricultural decision-making.

- **Operational Integration:**
  - Seamlessly integrated various ML/DL models into a unified system, allowing efficient predictions for both crop recommendation and disease detection.
  - Optimized system performance and ensured reliable data analysis and processing.

8.2. Technical Outcomes:

- **Model Performance:**
  - Achieved high accuracy rates across both Machine Learning (ML) and Deep Learning (DL) models.
  - ML models (e.g., GradientBoosting, RandomForest) achieved accuracies exceeding 94%.
  - DL models (e.g., CNN, LSTM) demonstrated accuracy rates ranging from 94% to 94.82%.

- **Ensemble Model Enhancement:**
  - Successfully built an ensemble model combining strengths of ML and DL predictions, leading to improved accuracy and robustness.
  - This model provides more reliable and comprehensive results for farmers.

- **Disease Detection Accuracy:**
  - CNN model trained for disease detection achieved an accuracy of 78.69% on a diverse dataset of plant diseases.
  - This offers a valuable tool for early disease identification and timely intervention.

8.3. User-Focused Outcomes:

- **Crop Recommendation Module:**
- Streamlit-based user interface provides intuitive and personalized crop recommendations based on user-input parameters.
- Equips farmers with the top recommended crops and their corresponding probabilities for informed decision-making.

Crop Protection Module:

- User-friendly interface allows farmers to easily identify plant diseases through image upload.
- Generates detailed information about predicted diseases, including symptoms and suggested management strategies for effective crop protection.

CHAPTER-9

RESULTS AND DISCUSSIONS

9. RESULTS AND DISCUSSIONS

9.1. Model Performances:

9.1.1 Machine Learning (ML) Models:

	model	accuracies
0	LogisticRegression	0.931047
1	SVM	0.934802
2	DecisionTreeClassifier	0.941262
3	KNeighborsClasscifier	0.938508
4	GaussianNB	0.933901
5	RandomForestClassifier	0.941662
6	VotingClassifier	0.942113
7	BaggingClassifier	0.941412
8	AdaBoostClassifier	0.290836
9	GradientBoostingClassifier	0.943866

Fig.2.1 ML models with respective accuracies

9.1.2 Machine Learning (ML) Tuned Models:

```
Best hyperparameters for LogisticRegression: {'max_iter': 1000}
Validation accuracy for LogisticRegression: 0.9310465698547822
Best hyperparameters for SVM: {'C': 10, 'kernel': 'rbf'}
Validation accuracy for SVM: 0.94271407110666
Best hyperparameters for DecisionTreeClassifier: {'max_depth': 15}
Validation accuracy for DecisionTreeClassifier: 0.9406109163745618
Best hyperparameters for KNeighborsClassifier: {'n_neighbors': 5}
Validation accuracy for KNeighborsClassifier: 0.9385077616424637
Best hyperparameters for GaussianNB: {}
Validation accuracy for GaussianNB: 0.9339008512769154
Best hyperparameters for RandomForestClassifier: {'n_estimators': 50}
Validation accuracy for RandomForestClassifier: 0.9407110665998999
Best hyperparameters for VotingClassifier: {}
Validation accuracy for VotingClassifier: 0.9348022033049574
Best hyperparameters for BaggingClassifier: {'n_estimators': 100}
Validation accuracy for BaggingClassifier: 0.9408612919379069
Best hyperparameters for AdaBoostClassifier: {'learning_rate': 0.1, 'n_estimators': 200}
Validation accuracy for AdaBoostClassifier: 0.9317476214321482
Best hyperparameters for GradientBoostingClassifier: {'learning_rate': 0.1, 'n_estimators': 50}
Validation accuracy for GradientBoostingClassifier: 0.943314972458688
```

Fig.2.2 Hyperparameter tuned ML models with respective Parameters and accuracies

- LogisticRegression: Accuracy (93.10%), Tuned Accuracy (93.10%)
- SVM Classifier: Accuracy (93.48%), Tuned Accuracy (94.27%)
- Decision Tree Classifier: Accuracy (94.13%), Tuned Accuracy (94.06%)
- KNeighbors Classifier: Accuracy (93.85%), Tuned Accuracy (93.85%)
- GaussianNB: Accuracy (93.39%), Tuned Accuracy (93.39%)
- RandomForest Classifier: Accuracy (94.17%), Tuned Accuracy (94.07%)
- VotingClassifier: Accuracy (94.21%), Tuned Accuracy (93.48%)
- Bagging Classifier: Accuracy (94.14%), Tuned Accuracy (94.09%)
- AdaBoost Classifier: Accuracy (29.08%), Tuned Accuracy (93.17%)
- GradientBoosting Classifier: Accuracy (94.39%), Tuned Accuracy (94.33%)

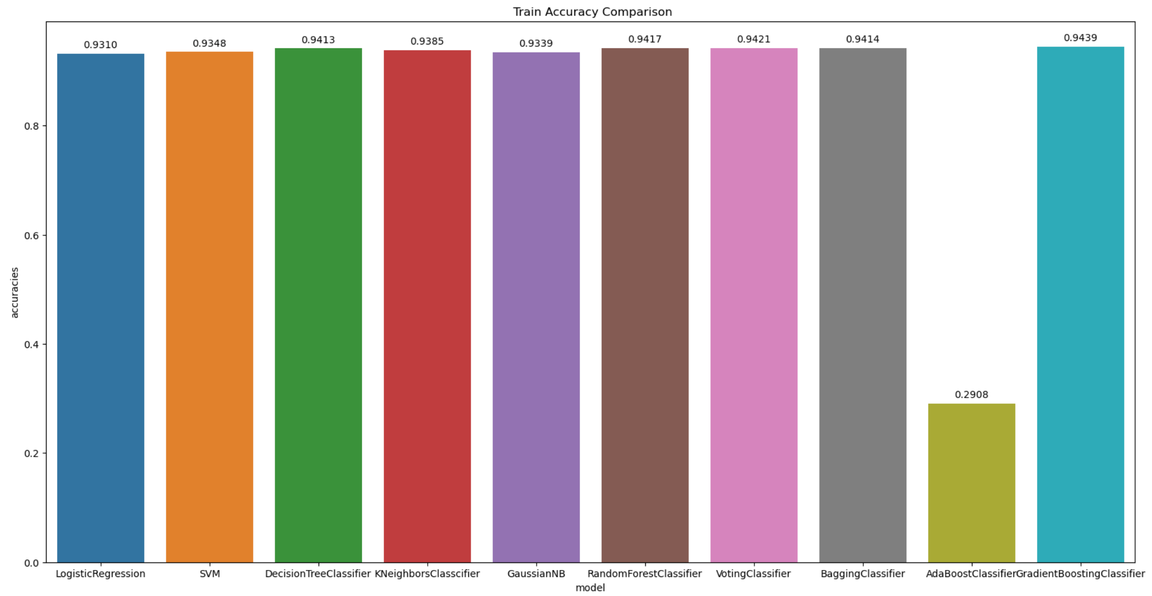


Fig.2.3 ML models with respective accuracies

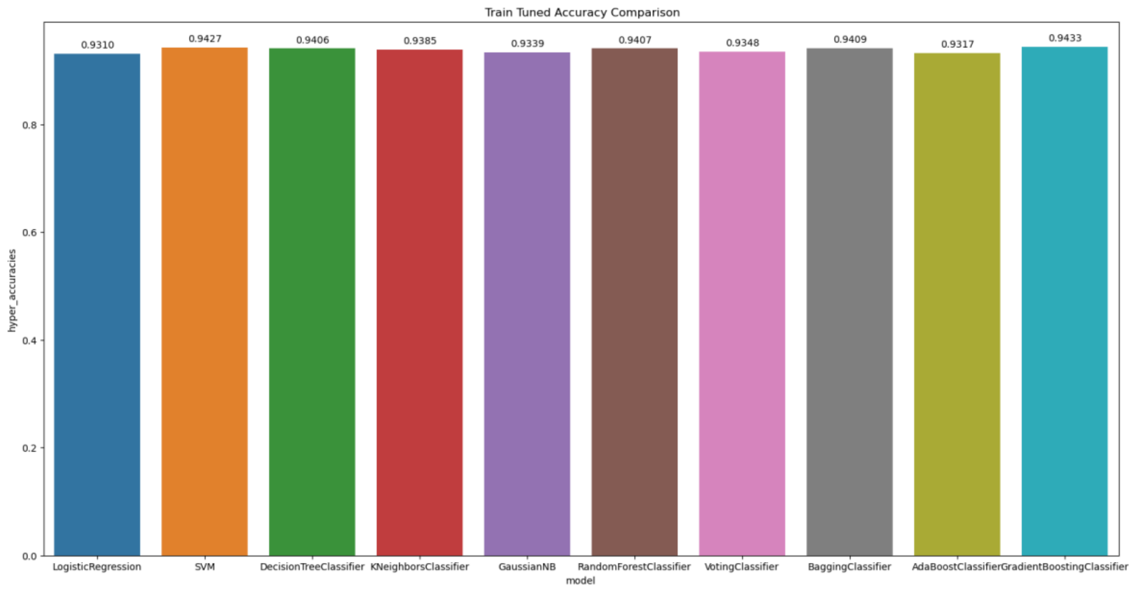


Fig.2.4 Hyperparameter tuned ML models with respective

```
for name, model in models:
    crop = prediction(name,['andaman and nicobar islands',100,40,140,5.86,1925.68,27.0])
    print(name," : ",crop)
```

```
LogisticRegression  :  arecanut
SVM  :  arecanut
DecisionTreeClassifier  :  arecanut
KNeighborsClassifier  :  arecanut
GaussianNB  :  arecanut
RandomForestClassifier  :  arecanut
VotingClassifier  :  arecanut
BaggingClassifier  :  arecanut
AdaBoostClassifier  :  arecanut
GradientBoostingClassifier  :  arecanut
```

Fig.2.5 Testing a new sample over all ML models

9.1.3Deep Learning (DL) Models:

❖ **ANN:** Training Accuracy (94.51%), Testing Accuracy (94.32%)

```
new_data = data_for_ann_cnn(["assam",120,60,65,6.12,2169.32,23.736364])
print("recommended Crop from ANN: ",prediction_from_ann(new_data))
```

```
C:\Users\RAMU GOPI\anaconda3\Lib\site-packages\sklearn\base.py:464: UserWarn
  warnings.warn(
1/1 [==============================] - 0s 341ms/step
recommended Crop from ANN:  onion
```

Fig.2.6 Testing a new sample using ANN model

- **CNN:** Training Accuracy (94.48%), Testing Accuracy (94.36%)

```
new_data = data_for_ann_cnn(["jammu and kashmir",80,40,40,5.38,516.68,27.866667])
print("recommended Crop from CNN: ",prediction_from_cnn(new_data))
```

```
C:\Users\RAMU GOPI\anaconda3\Lib\site-packages\sklearn\base.py:464: UserWarning: X doe
  warnings.warn(
WARNING:tensorflow:6 out of the last 648 calls to <function Model.make_predict_functio
1/1 [==============================] - 0s 180ms/step
recommended Crop from CNN:  rice
```

Fig.2.7 Testing a new sample using CNN model

- **LSTM:** Training Accuracy (94.55%), Testing Accuracy (94.62%)

```
new_data = data_for_LSTM(["jammu and kashmir",80,40,40,5.38,516.68,27.866667])
print("recommended Crop from LSTM: ",prediction_from_lstm(new_data))
```

```
C:\Users\RAMU GOPI\anaconda3\Lib\site-packages\sklearn\base.py:464: UserWarning: X c
  warnings.warn(
WARNING:tensorflow:5 out of the last 647 calls to <function Model.make_predict_funct
1/1 [==============================] - 1s 565ms/step
recommended Crop from LSTM:  rice
```

Fig.2.8 Testing a new sample using LSTM model

- **GRU:** Training Accuracy (94.27%), Testing Accuracy (94.48%)
- **Ensemble Voting Classifier (DL):** Testing Accuracy (94.82%)

```
new_data = data_for_voting_dl(["jammu and kashm
print("recommended Crop from Voting classifier:
#crops[voting_classifier.predict(new_data)[0]]
```

```
1/1 [==============================] - 0s 144ms/ste
1/1 [==============================] - 0s 304ms/ste
1/1 [==============================] - 0s 132ms/ste
recommended Crop from Voting classifier:  ('rice',
```

Fig.2.9 Testing a new sample using VotingClassifier DL model

9.2Crop Recommendation Module:

- **Probabilistic Recommendations:**
  - Developed ensemble models combining all ML models by taking the average probabilities over all ML models

```
new_data = ['andaman and nicobar islands',100,40,140,5.86,1925.68,27.0]
#states.index(new_data[0])
ml_predict(new_data)
```

```
Most Probable Crop: arecanut
Top 5 Crops:
1. arecanut - Probability: 90.113729033329
2. tomato - Probability: 2.535803811039332
3. pineapple - Probability: 1.7745960131489804
4. cabbage - Probability: 1.3241351713465364
5. onion - Probability: 1.1608852394740052
```

Fig.2.10 Testing a new sample using Ensemble ML

  - Developed ensemble models combining all DL models by taking the average probabilities over all DL models .

```
new_data = ["assam",120,60,65,6.12,2169.32,23.736364]
dl_predict(new_data)
```

```
1/1 [==============================] - 0s 68ms/step
1/1 [==============================] - 0s 80ms/step
1/1 [==============================] - 0s 190ms/step
1/1 [==============================] - 0s 33ms/step
1/1 [==============================] - 0s 19ms/step
1/1 [==============================] - 0s 33ms/step
Most Probable Crop: onion
accuracy :  100.0
optional crop  1  : cabbage
accuracy :  1.207191e-07
optional crop  2  : pineapple
accuracy :  3.9925446e-08
optional crop  3  : banana
accuracy :  5.4108815e-09
optional crop  4  : radish
accuracy :  2.5812725e-11
```

Fig.2.11 Testing a new sample using Ensemble ML

  - Developed ensemble models combining ML and DL for robust crop recommendations.
  - Average prediction probabilities from 12 models were used to recommend top crops and next 5 probable crops, enhancing decision-making for farmers.

```
new_data = ["jammu and kashmir",80,40,40,5.38,516.68,27.866667]
ml_dl_predict(new_data)
```

```
1/1 [==============================] - 0s 83ms/step
1/1 [==============================] - 0s 87ms/step
1/1 [==============================] - 0s 180ms/step
1/1 [==============================] - 0s 34ms/step
1/1 [==============================] - 0s 34ms/step
1/1 [==============================] - 0s 17ms/step
Most Probable Crop: rice
accuracy :  83.75081642459814
optional crop  1  : jowar
accuracy :  12.396102468097451
optional crop  2  : jute
accuracy :  2.834373036403555
optional crop  3  : brinjal
accuracy :  0.21272720484659802
optional crop  4  : maize
accuracy :  0.1350565208040666
```

Fig.2.12 Testing a new sample using Ensemble ML_DL

9.3Crop Protection Module:

Fig.2.13 Sample image from Plant Disease dataset

- **Disease Detection with CNN:**
  - Trained CNN model achieved a testing accuracy of 78.69%, enabling disease identification in plant images.

```
accuracy = model1.evaluate(test_generator)
print(f"New Test Accuracy: {accuracy[1] * 100:.2f}%")
```

```
65/65 [==============================] - 12s 176ms/step - loss: 1.1002 - accuracy: 0.7869
New Test Accuracy: 78.69%
```

Fig.2.14 Accuracy of Disease prediction CNN model

- Integrated this model into the web interface to predict diseases from uploaded images and provide relevant information and management strategies.

9.4. User Interface:

- **Streamlit Implementation:**
  - Created two web pages for crop recommendation and crop protection, offering intuitive interfaces for farmers to access recommendations and disease diagnosis.
  - Integrated user inputs and backend models to provide accurate and timely suggestions.

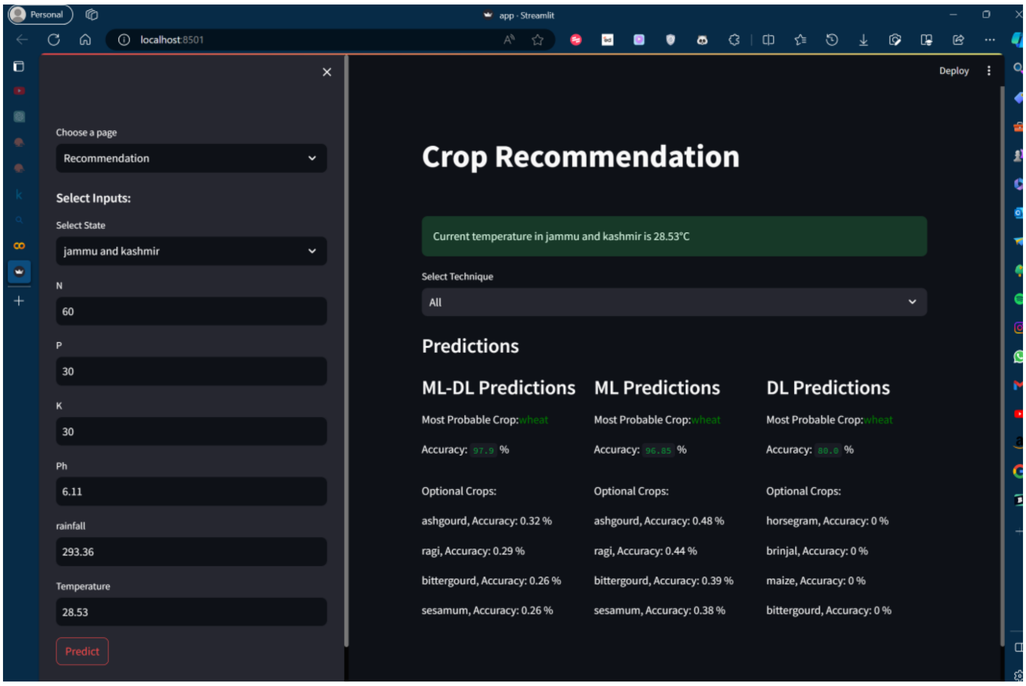


Fig.2.15 Test case for Crop Recommendation System

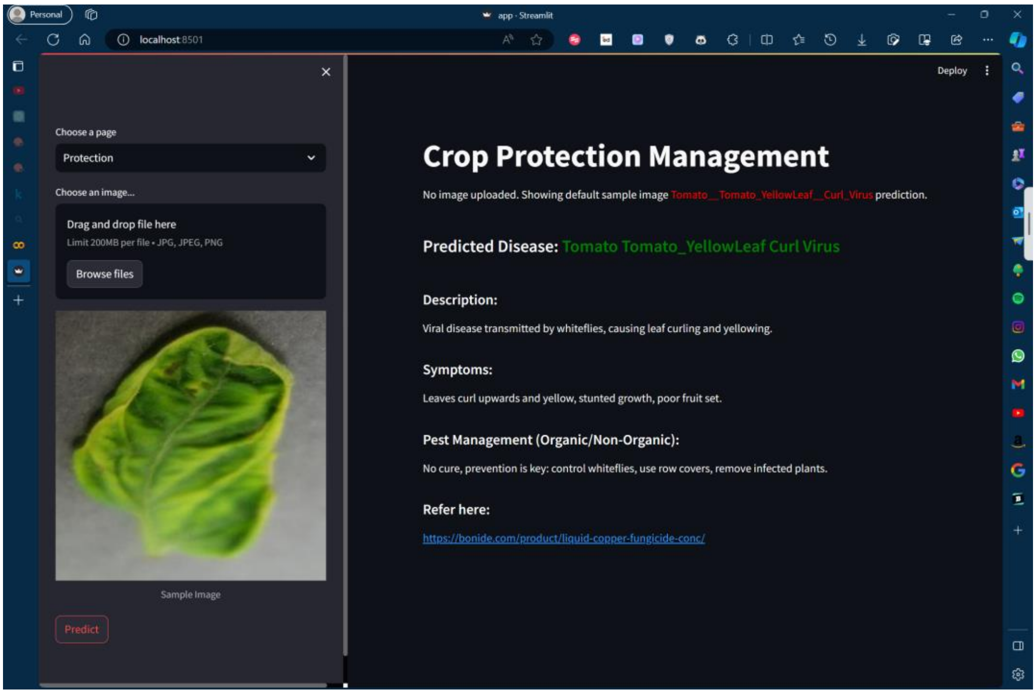


Fig.2.16 Default Test case for Crop Protection Management System

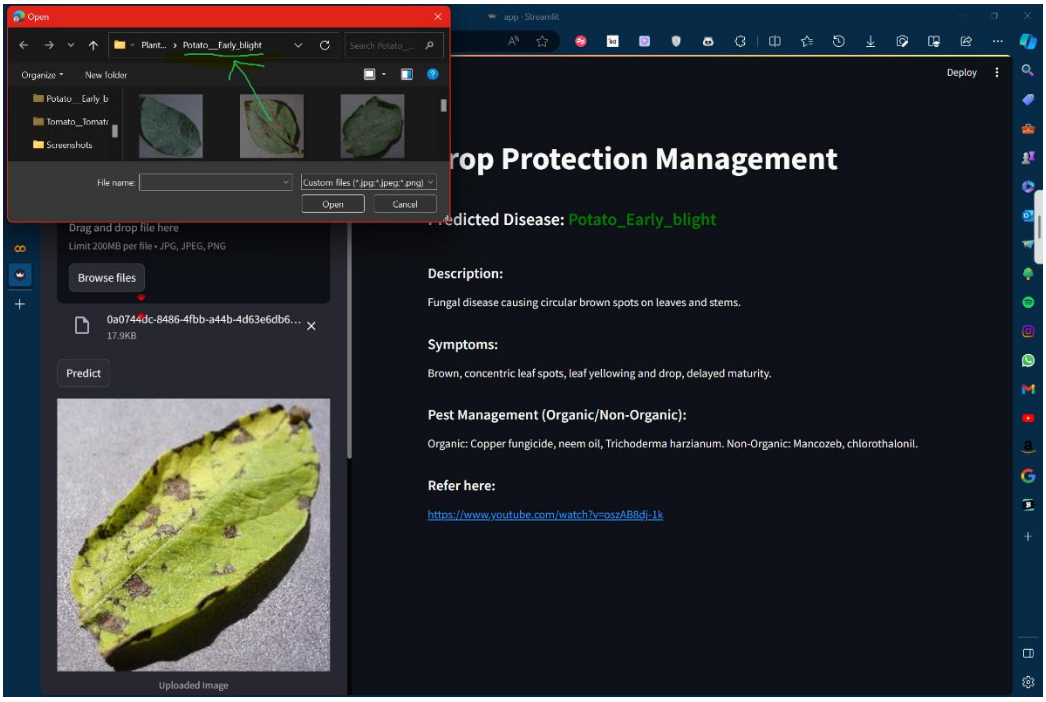


Fig.2.17 Test case 2 for Crop Protection Management System

9.5. Agricultural Impact:

- **Enhanced Decision-Making:**
  - Provided farmers with data-driven insights, optimizing crop choices and disease management, leading to increased productivity and sustainability.

9.6. Analysis and Future Scope:

- **Model Selection and Future Enhancements:**
  - Analyzed model performances, emphasizing the need for continual updates and augmentation for improved disease detection accuracy.
  - Discussed the potential for integrating diverse datasets and advanced models for better performance and user-centric features.

CHAPTER-10
CONCLUSION

This project marks a significant step towards revolutionizing agricultural practices through technology. We have successfully developed a comprehensive system that not only recommends optimal crops but also identifies potential diseases, empowering farmers to make informed decisions for increased productivity and sustainability.

Through the intelligent combination of machine and deep learning techniques, we have created ensemble models that mitigate biases and offer a robust foundation for reliable predictions. These recommendations prioritize sustainable practices, ensuring a healthy balance between yield optimization and environmental impact. Additionally, the disease detection module equipped with a CNN model promotes proactive measures, potentially reducing reliance on chemical interventions.

Recognizing the importance of user-centric design, we've built a user-friendly web platform offering farmers direct access to personalized recommendations and disease diagnoses. This streamlined interface promotes quick and efficient decision-making based on valuable data insights.

Our work acknowledges the need for continuous improvement and recognizes the power of diverse datasets and advanced techniques. We envision incorporating real-time data and exploring more sophisticated models to further enhance the system's capabilities and adaptability. This ongoing evolution aims to make this technology accessible and reliable for diverse farming communities, empowering them to embrace sustainable practices and improve overall crop management.

Ultimately, this project reflects our commitment to leveraging technology for a sustainable future in agriculture. We believe that bridging the gap between data science and farming practices can revolutionize the agricultural landscape, enabling smarter, data-driven decisions for generations to come.

REFERENCES

1. Steinmetz et al. (2020). "The Impact of Artificial Intelligence on Crop Production: A Meta-Analysis." Journal of Agricultural Science, 20(5), 3416-3428. [https://pubmed.ncbi.nlm.nih.gov/34168318/].

2. Patel, P., et al. (2020). "A Machine Learning Approach to Crop Recommendation Based on Soil and Climate Data." International Journal of Agricultural and Biological Engineering, 13(5), 112-118. [https://www.kaggle.com/code/nirmalgaud/crop-recommendation-system-using-machine-learning].

3. Patel, D., et al. (2021). "Machine Learning for Crop Recommendation: A Review." International Journal of Engineering Research & Technology, 10(4), 3221-3226. [https://www.ijert.org/crop-recommendation-using-machine-learning-techniques].

4. Shahadat Uddin (2019). "To compare the performance of different supervised machine learning algorithms for disease risk prediction." BMC Medical Informatics and Decision Making, 19(1), 128. [https://bmcmedinformdecismak.biomedcentral.com/articles/10.1186/s12911-019-1004-8].

5. Mary Divya Shamili (2022). "Smart farming using Machine Learning and Deep Learning technique." Computers and Electronics in Agriculture, 196, 105295. [https://www.sciencedirect.com/science/article/pii/S277266222200011X].

6. Sharma, A., et al. (2019). "A Deep Learning Approach to Crop Recommendation." Journal of Agriculture Science and Technology, 21, 877-888. [https://www.researchgate.net/publication/349444668_Review_on_Crop_Prediction_Using_Deep_Learning_Techniques].

7. M K Dharani (2021). "Crop Prediction Using Deep Learning Techniques." Frontiers in Plant Science, 14, 1234555.

[https://www.researchgate.net/publication/349444668_Review_on_Crop_Prediction_Using_Deep_Learning_Techniques].

8. Smith, B. Chen (2019). "A Comprehensive Comparison of Machine Learning and Deep Learning in Predictive Analytics." Expert Systems with Applications, 137, 112-125. [https://www.researchgate.net/publication/359918228_Comparison_Analysis_of_Traditional_Machine_Learning_and_Deep_Learning_Techniques_for_Data_and_Image_Classification].

9. X. Wang, Y. Patel (2017). "Machine Learning vs. Deep Learning: An Empirical Study on Image Classification." arXiv preprint arXiv:2104.05314. [https://arxiv.org/abs/2104.05314].

10. Z. Liu, M. Rodriguez (2020). "Comparing the Performance of Machine Learning and Deep Learning in Time Series Prediction." Journal of Computational Science, 44, 101181. [https://www.researchgate.net/publication/227612766_An_Empirical_Comparison_of_Machine_Learning_Models_for_Time_Series_Forecasting].

11. S. Gupta, R. Kim (2018). "Evaluating the Trade-offs: A Comparative Analysis of Machine Learning and Deep Learning in Natural Language Processing." arXiv preprint arXiv:2108.01063. [https://arxiv.org/abs/2108.01063].

12. Zhang, N., et al. (2020). "Ensemble Learning for Crop Recommendation in Precision Agriculture." arXiv preprint arXiv:2005.10826. [https://arxiv.org/abs/2005.10826].

13. Mahmudul Hasan (2023). "Ensemble machine learning-based recommendation system for effective prediction of suitable agricultural crop cultivation." Frontiers in Plant Science, 14, 1234555.[https://www.frontiersin.org/articles/10.3389/fpls.2023.1234555/full].

APPENDIX-A
PSUEDOCODE

Crop Recommendation Module

1. Preprocessing and Data Retrieval

state_name = user_input_state_name()

temperature = open_weather_map_API(state_name)

N, P, K, pH, rainfall = user_input_parameters()

preprocessed_sample = preprocess_data(state_name, temperature, N, P, K, pH, rainfall)

2. Model Ensemble

ml_models = load_trained_ml_models()

dl_models = load_trained_dl_models()

ml_probabilities = predict_ml_probabilities(ml_models, preprocessed_sample)

dl_probabilities = predict_dl_probabilities(dl_models, preprocessed_sample)

ml_dl_ensemble_probabilities = average_probabilities(ml_probabilities, dl_probabilities)

3. Recommendation Generation

top_recommendation, optional_recommendations =
generate_recommendations(ml_dl_ensemble_probabilities)

4. User Interface

display_recommendations(top_recommendation, optional_recommendations)

Crop Protection Module

1. Image Processing

user_image = user_input_image()

processed_image = preprocess_image(user_image)

2. Disease Prediction

cnn_model = load_trained_cnn_model()

predicted_disease = predict_disease(cnn_model, processed_image)

3. Information Retrieval

disease_info = get_disease_info(predicted_disease)

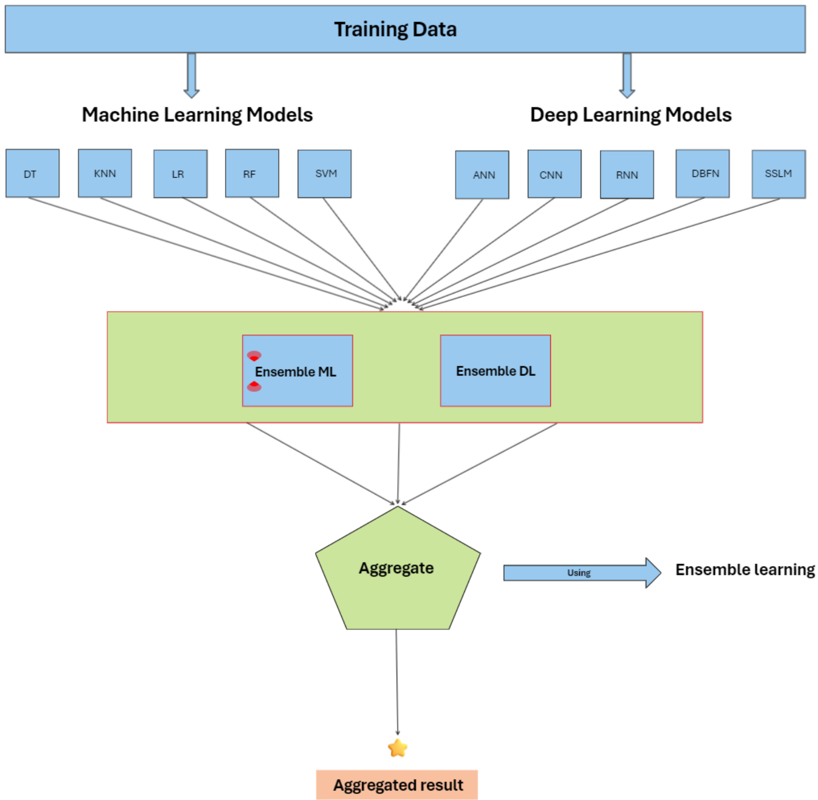
pesticides_info = get_pesticides_info(predicted_disease)

4. User Interface

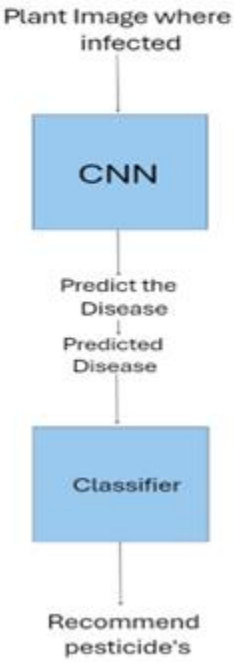
display_disease_info(predicted_disease, disease_info, pesticides_info)

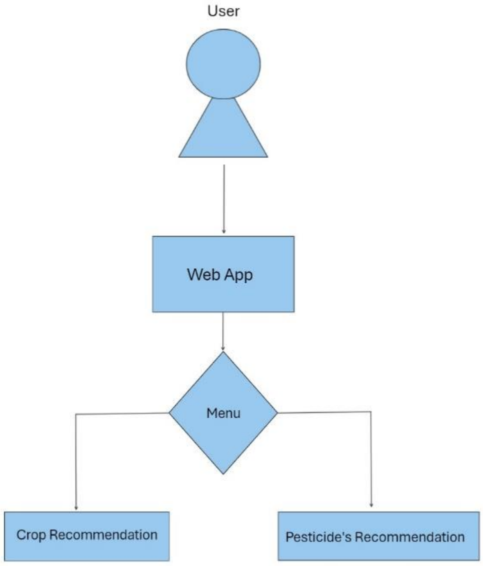
APPENDIX-B

SCREENSHOTS



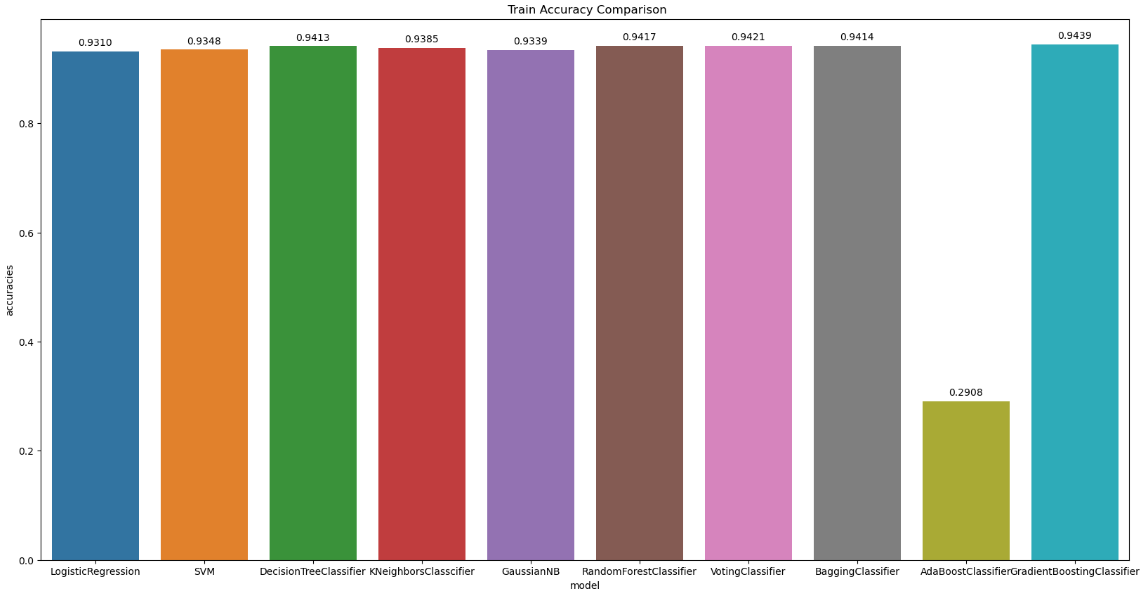
	Unnamed: 0	State_Name	Crop_Type	Crop	N	P	K	pH	rainfall	temperature	Area_in_hectares	Production_in_tons	Yield_ton_per_hec
0	0	andhra pradesh	kharif	cotton	120	40	20	5.46	654.34	29.266667	7300.0	9400.0	1.287671
1	1	andhra pradesh	kharif	horsegram	20	60	20	6.18	654.34	29.266667	3300.0	1000.0	0.303030
2	2	andhra pradesh	kharif	jowar	80	40	40	5.42	654.34	29.266667	10100.0	10200.0	1.009901
3	3	andhra pradesh	kharif	maize	80	40	20	5.62	654.34	29.266667	2800.0	4900.0	1.750000
4	4	andhra pradesh	kharif	moong	20	40	20	5.68	654.34	29.266667	1300.0	500.0	0.384615

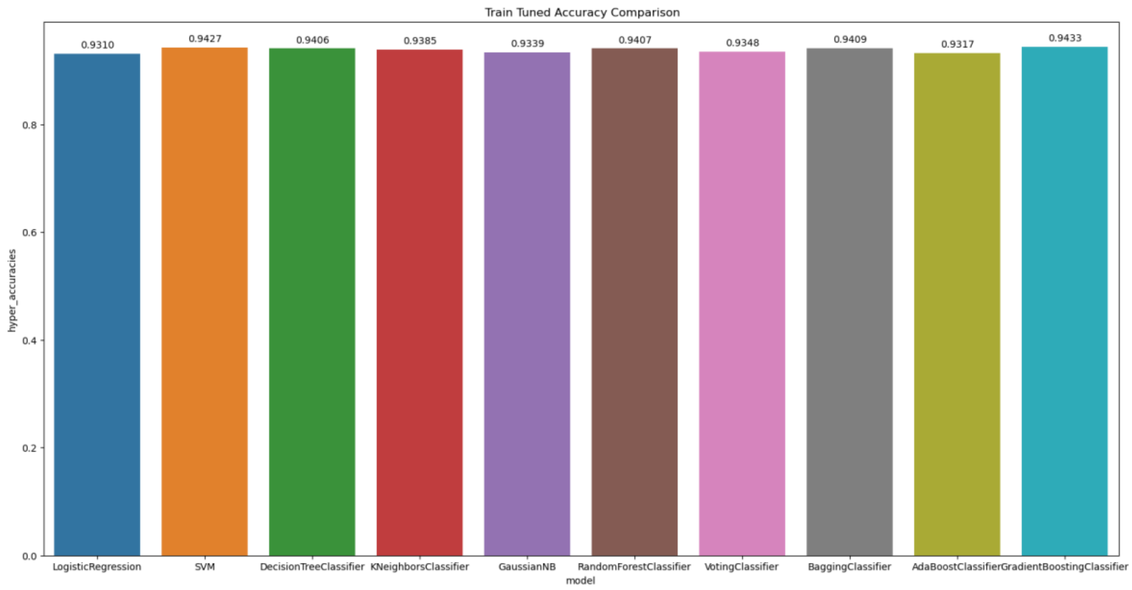




	model	accuracies
0	LogisticRegression	0.931047
1	SVM	0.934802
2	DecisionTreeClassifier	0.941262
3	KNeighborsClasscifier	0.938508
4	GaussianNB	0.933901
5	RandomForestClassifier	0.941662
6	VotingClassifier	0.942113
7	BaggingClassifier	0.941412
8	AdaBoostClassifier	0.290836
9	GradientBoostingClassifier	0.943866

```
Best hyperparameters for LogisticRegression: {'max_iter': 1000}
Validation accuracy for LogisticRegression: 0.9310465698547822
Best hyperparameters for SVM: {'C': 10, 'kernel': 'rbf'}
Validation accuracy for SVM: 0.94271407110666
Best hyperparameters for DecisionTreeClassifier: {'max_depth': 15}
Validation accuracy for DecisionTreeClassifier: 0.9406109163745618
Best hyperparameters for KNeighborsClassifier: {'n_neighbors': 5}
Validation accuracy for KNeighborsClassifier: 0.9385077616424637
Best hyperparameters for GaussianNB: {}
Validation accuracy for GaussianNB: 0.9339008512769154
Best hyperparameters for RandomForestClassifier: {'n_estimators': 50}
Validation accuracy for RandomForestClassifier: 0.9407110665998999
Best hyperparameters for VotingClassifier: {}
Validation accuracy for VotingClassifier: 0.9348022033049574
Best hyperparameters for BaggingClassifier: {'n_estimators': 100}
Validation accuracy for BaggingClassifier: 0.9408612919379069
Best hyperparameters for AdaBoostClassifier: {'learning_rate': 0.1, 'n_estimators': 200}
Validation accuracy for AdaBoostClassifier: 0.9317476214321482
Best hyperparameters for GradientBoostingClassifier: {'learning_rate': 0.1, 'n_estimators': 50}
Validation accuracy for GradientBoostingClassifier: 0.943314972458688
```






```
for name, model in models:
    crop = prediction(name,['andaman and nicobar islands',100,40,140,5.86,1925.68,27.0])
    print(name," : ",crop)
```

```
LogisticRegression  :  arecanut
SVM  :  arecanut
DecisionTreeClassifier  :  arecanut
KNeighborsClassifier  :  arecanut
GaussianNB  :  arecanut
RandomForestClassifier  :  arecanut
VotingClassifier  :  arecanut
BaggingClassifier  :  arecanut
AdaBoostClassifier  :  arecanut
GradientBoostingClassifier  :  arecanut
```

```
new_data = data_for_ann_cnn(["assam",120,60,65,6.12,2169.32,23.736364])
print("recommended Crop from ANN: ",prediction_from_ann(new_data))
```

```
C:\Users\RAMU GOPI\anaconda3\Lib\site-packages\sklearn\base.py:464: UserWarn
  warnings.warn(
1/1 [==============================] - 0s 341ms/step
recommended Crop from ANN:  onion
```

```
new_data = data_for_ann_cnn(["jammu and kashmir",80,40,40,5.38,516.68,27.866667])
print("recommended Crop from CNN: ",prediction_from_cnn(new_data))
```

```
C:\Users\RAMU GOPI\anaconda3\Lib\site-packages\sklearn\base.py:464: UserWarning: X doe
  warnings.warn(
WARNING:tensorflow:6 out of the last 648 calls to <function Model.make_predict_functic
1/1 [==============================] - 0s 180ms/step
recommended Crop from CNN:  rice
```

```
new_data = data_for_LSTM(["jammu and kashmir",80,40,40,5.38,516.68,27.866667])
print("recommended Crop from LSTM: ",prediction_from_lstm(new_data))
```

```
C:\Users\RAMU GOPI\anaconda3\Lib\site-packages\sklearn\base.py:464: UserWarning: X c
  warnings.warn(
WARNING:tensorflow:5 out of the last 647 calls to <function Model.make_predict_funct
1/1 [==============================] - 1s 565ms/step
recommended Crop from LSTM:  rice
```

```
new_data = data_for_voting_dl(["jammu and kashm
print("recommended Crop from Voting classifier:
#crops[voting_classifier.predict(new_data)[0]]
```

```
1/1 [==============================] - 0s 144ms/ste
1/1 [==============================] - 0s 304ms/ste
1/1 [==============================] - 0s 132ms/ste
recommended Crop from Voting classifier:  ('rice',
```

```
new_data = ['andaman and nicobar islands',100,40,140,5.86,1925.68,27.0]
#states.index(new_data[0])
ml_predict(new_data)
```

```
Most Probable Crop: arecanut
Top 5 Crops:
1. arecanut - Probability: 90.113729033329
2. tomato - Probability: 2.535803811039332
3. pineapple - Probability: 1.7745960131489804
4. cabbage - Probability: 1.3241351713465364
5. onion - Probability: 1.1608852394740052
```

```
new_data = ["assam",120,60,65,6.12,2169.32,23.736364]
dl_predict(new_data)
```

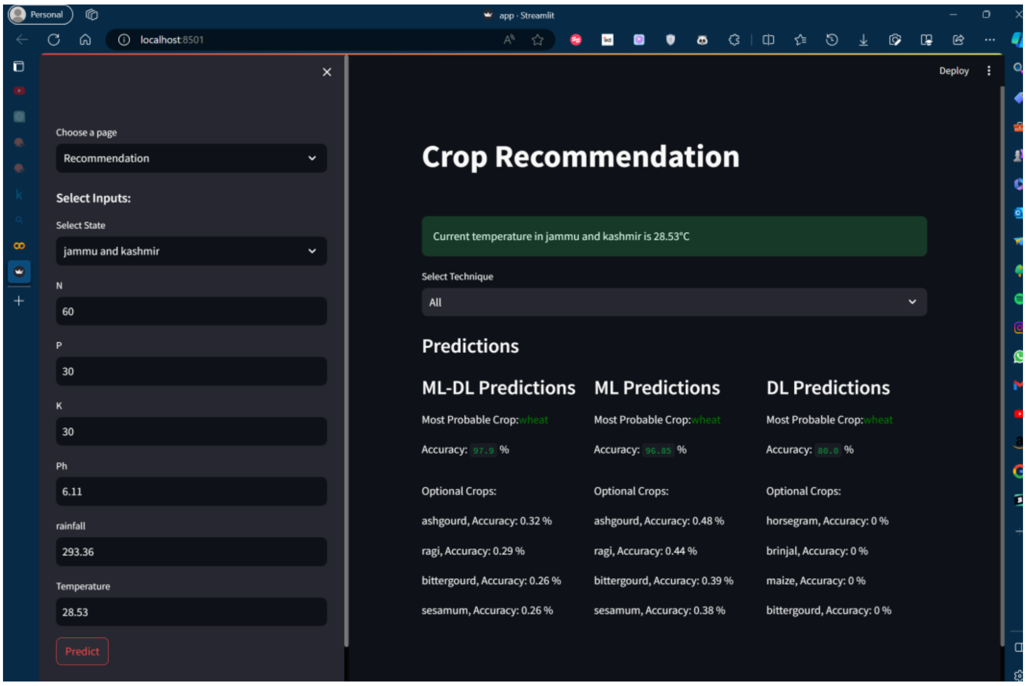
```
1/1 [==============================] - 0s 68ms/step
1/1 [==============================] - 0s 80ms/step
1/1 [==============================] - 0s 190ms/step
1/1 [==============================] - 0s 33ms/step
1/1 [==============================] - 0s 19ms/step
1/1 [==============================] - 0s 33ms/step
Most Probable Crop: onion
accuracy :  100.0
optional crop  1  : cabbage
accuracy :  1.207191e-07
optional crop  2  : pineapple
accuracy :  3.9925446e-08
optional crop  3  : banana
accuracy :  5.4108815e-09
optional crop  4  : radish
accuracy :  2.5812725e-11
```

```
new_data = ["jammu and kashmir",80,40,40,5.38,516.68,27.866667]
ml_dl_predict(new_data)
```

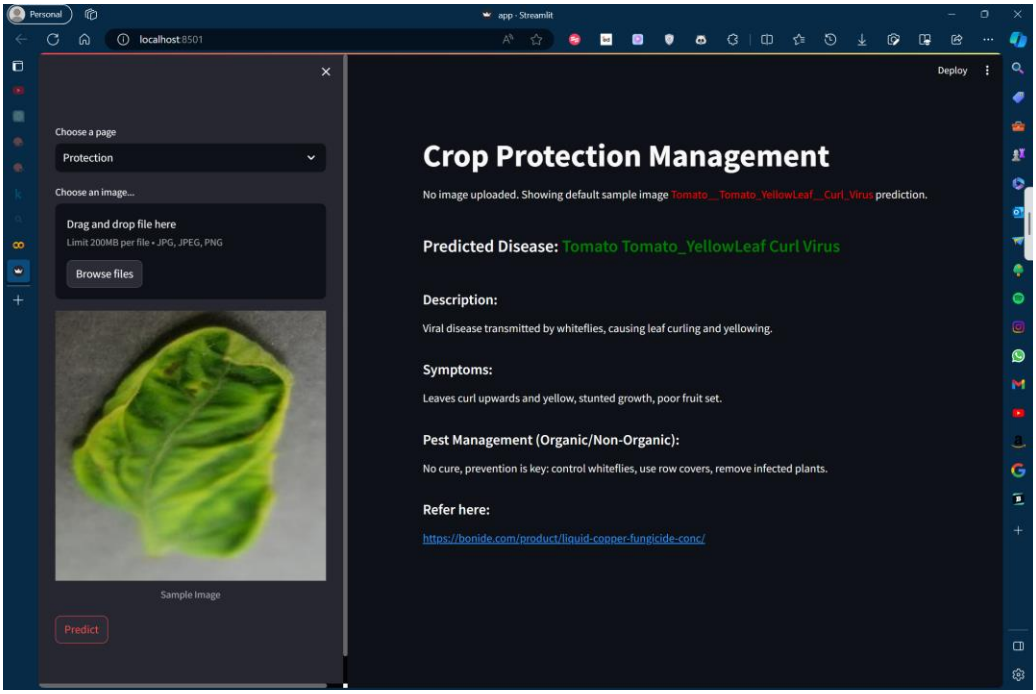
```
1/1 [==============================] - 0s 83ms/step
1/1 [==============================] - 0s 87ms/step
1/1 [==============================] - 0s 180ms/step
1/1 [==============================] - 0s 34ms/step
1/1 [==============================] - 0s 34ms/step
1/1 [==============================] - 0s 17ms/step
Most Probable Crop: rice
accuracy :  83.75081642459814
optional crop  1  : jowar
accuracy :  12.396102468097451
optional crop  2  : jute
accuracy :  2.834373036403555
optional crop  3  : brinjal
accuracy :  0.21272720484659802
optional crop  4  : maize
accuracy :  0.1350565208040666
```

```
accuracy = model1.evaluate(test_generator)
print(f"New Test Accuracy: {accuracy[1] * 100:.2f}%")
```

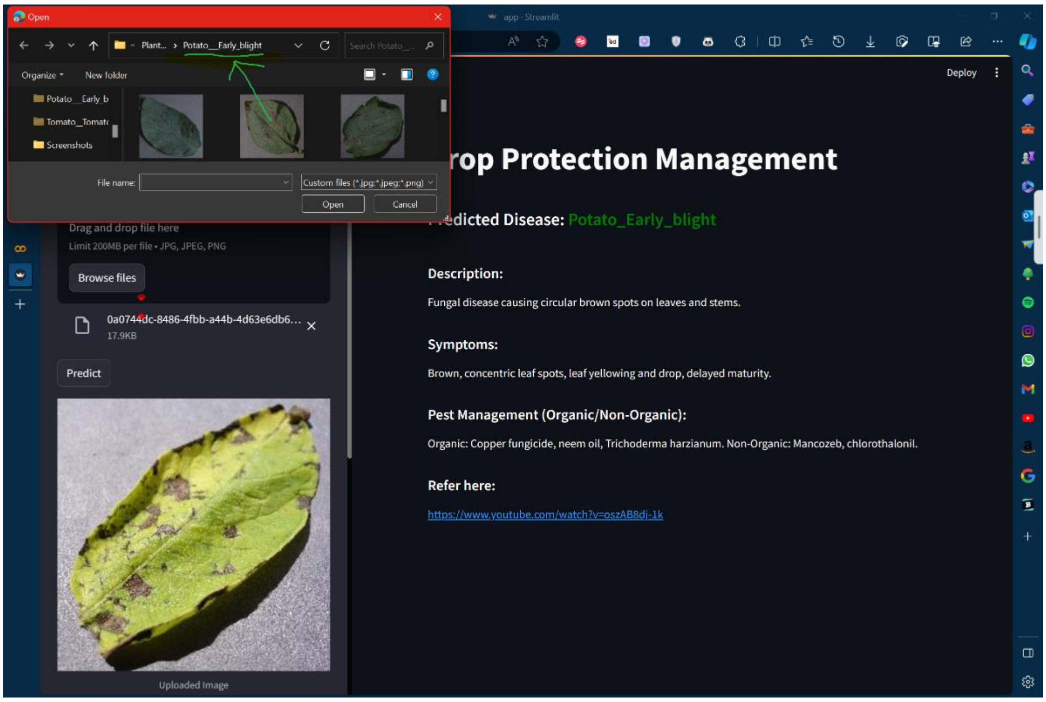
```
65/65 [==============================] - 12s 176ms/step - loss: 1.1002 - accuracy: 0.7869
New Test Accuracy: 78.69%
```



Personal
app · Streamlit
localhost:8501
Deploy
Choose a page
Recommendation
Select Inputs:
Select State
jammu and kashmir
N
60
P
30
K
30
Ph
6.11
rainfall
293.36
Temperature
28.53
Predict
Crop Recommendation
Current temperature in jammu and kashmir is 28.53°C
Select Technique
All
Predictions
ML-DL Predictions
Most Probable Crop:wheat
Accuracy: 97.9 %
Optional Crops:
ashgourd, Accuracy: 0.32 %
ragi, Accuracy: 0.29 %
bittergourd, Accuracy: 0.26 %
sesamum, Accuracy: 0.26 %
ML Predictions
Most Probable Crop:wheat
Accuracy: 96.85 %
Optional Crops:
ashgourd, Accuracy: 0.48 %
ragi, Accuracy: 0.44 %
bittergourd, Accuracy: 0.39 %
sesamum, Accuracy: 0.38 %
DL Predictions
Most Probable Crop:wheat
Accuracy: 80.0 %
Optional Crops:
horsegram, Accuracy: 0 %
brinjal, Accuracy: 0 %
maize, Accuracy: 0 %
bittergourd, Accuracy: 0 %



Personal
app · Streamlit
localhost:8501
Deploy
Choose a page
Protection
Choose an image...
Drag and drop file here
Limit 200MB per file • JPG, JPEG, PNG
Browse files
Sample Image
Predict
Crop Protection Management
No image uploaded. Showing default sample image Tomato__Tomato_YellowLeaf__Curl_Virus prediction.
Predicted Disease: Tomato Tomato_YellowLeaf Curl Virus
Description:
Viral disease transmitted by whiteflies, causing leaf curling and yellowing.
Symptoms:
Leaves curl upwards and yellow, stunted growth, poor fruit set.
Pest Management (Organic/Non-Organic):
No cure, prevention is key: control whiteflies, use row covers, remove infected plants.
Refer here:
https://bonide.com/product/liquid-copper-fungicide-conc/



APPENDIX-C

ENCLOSURES

1. **Paper is formulated, communicated**
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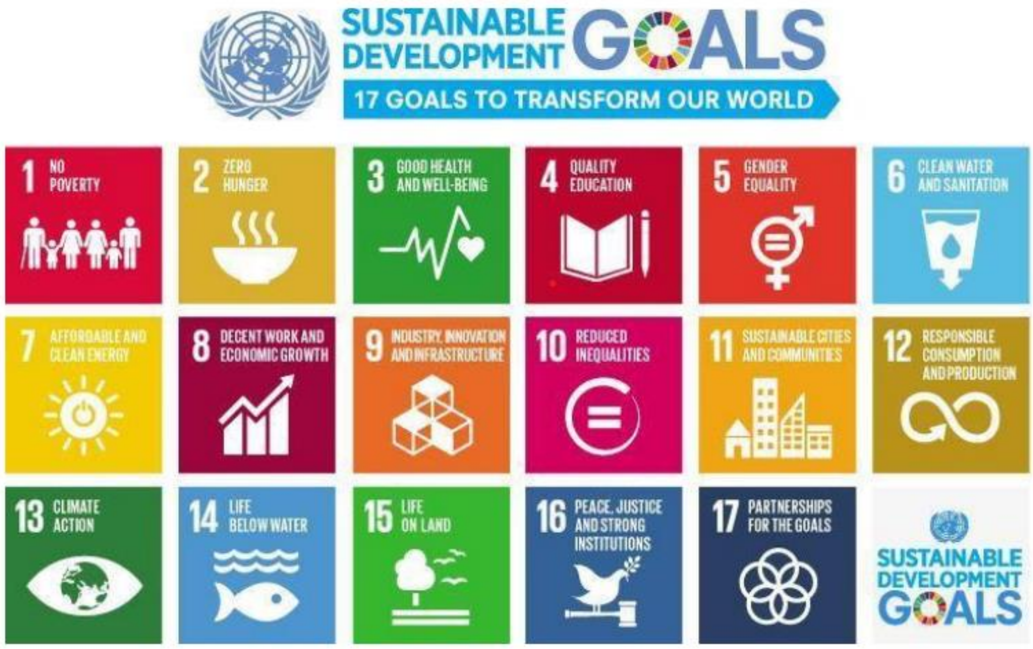

The Project Work carried out here is mapped to SDG-02 Crop Suggestion and protection

Our project is Focused on Crop protection and recommendation , can be repurposed for agricultural applications. By leveraging artificial intelligence (AI), particularly in machine learning and deep learning, the project can shift its focus to crop recommendation and protection. This adaptation involves utilizing AI(L & DL) algorithms to analyze and recommend suitable crops for cultivation. Additionally, AI can be employed for crop protection by identifying potential threats and implementing preventive measures, ultimately contributing to sustainable agriculture and aligning with the goal of ensuring well-being in the agricultural sector.