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Harvest Helper: Maximizing Crop Yields With Data-Driven Recommendations

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Abstract: Agriculture forms the backbone of India's economy, with a significant portion of the population reliant on it for livelihood. However, despite its importance, farmers face numerous challenges in optimizing crop selection and fertilizer management to maximize yield rates. This project addresses these challenges by implementing an intelligent system aimed at assisting farmers in making informed decisions regarding crop selection and fertilizer usage. The project also focuses on user interface development, incorporating a user-friendly interface tailored for farmers' ease of use. Through comprehensive testing, validation, and continuous improvement efforts, the system aims to revolutionize agricultural practices, ultimately contributing to increased crop yields, reduced input costs, and improved livelihoods for farming communities.

Keywords— Harvest Helper – Agriculture System, Centralized Database, Central Government Websites Access, Crop Recommendation, Interface Between Farmers And Digital Crop Recommendation.

I. Introduction

India is an agricultural nation, where the population is over 1.2 billion, out of which around 70% of the population depends upon agriculture. Agriculture is a primary source of earning for Indian citizens and agriculture also has made an influence on India's economy. Agriculturists have an immeasurable variety to choose equitable products of the soil crops The selection of the crop by the farmer plays a vital role in the economical returns to the farmer. In this project, we have implemented an intelligent system which intends to assist the farmers in making an informed decision about which crop to grow and which fertilizer used depending on the soil characteristics as well as environmental factors such as temperature and rainfall. In the crop recommendation application, the user can provide the soil data from their side and the application will predict which crop should the user grow. For the fertilizer recommendation application, the user can input the soil data and the type of crop they are growing, and the application will predict what the soil lacks or has excess of and will recommend improvements.

A. **Problem Definition Problem Identified:** Addressing Challenges in Agricultural Optimization. Despite advancements in agricultural technology, farmers still face challenges in optimizing crop selection and fertilizer management to maximize yield rates. Existing methods often lack precision and fail to consider the intricate relationship between environmental factors, soil nutrient content, and crop suitability. This project aims to address these challenges by 3 developing a comprehensive system that leverages data analysis techniques to provide tailored crop recommendations based on soil nutrients, rainfall, humidity, and temperature.

B. Objectives of the Study: This research aims to develop a secure, scalable, and userfriendly Farmer Helper Website that: 1. To provide data-driven crop recommendations, the system will analyze soil nutrient levels, rainfall patterns, temperature ranges, and other environmental factors to suggest the most suitable crops for the user's specific agricultural context. 2. To optimize fertilizer usage and enhance crop

productivity, the system will develop algorithms to predict the optimal fertilizer type and application rates based on the crop's nutrient requirements and the soil's existing composition.

II. **RELATED WORK**: CROP RECOMMENDATION SYSTEM USING MACHINE LEARNING Study 1: In this project, the

authors used various machine learning algorithms for crop recommendation, including Decision Tree, Naive Bayes, Support Vector Machine, Logistic Regression, Random Forest, and XGBoost. The highest accuracy of 99.31% was achieved using the XGBoost algorithm on a dataset containing information about 22 different crops . Study 2: In this study, two machine learning algorithms, Random Forest and Decision Tree, were employed for supervised learning tasks involving classification and regression problems. Random Forest, which leverages the ensemble learning technique, utilizes multiple decision trees trained on random subsets of data and averages their predictions to improve model accuracy and reduce overfitting.

| Sr No | Title | IEEE | Algorithms | Parameters | Findings | Limitations |
|----------|--|---|---|--|---|---|
| No . 1 | Crop Predicti on using Machi ne Learning | This paper is published in IRE Journals, Volume 6,Issue 9(March 2023) | crop prediction: K- Nearest Neighbors (KNN) Decision Tree Random Forest The Decision Tree algorithm was | The mod el considers various environment al and soil parameters, including: Soil Nutrients: Nitrogen (N), Phosphorus (P), Potassium (K) Weather Parameters: Temperature, | choose the best crop based on soil and weath er conditions. | accuracy of predictio ns depends on the quality and availability of |
| | | | accurate and was selected for final | Humidity, Rainfall Soil Condition: pH value | | input data manually, which may lead to errors. |
| 2 | A Machi ne Learning Approach for Crop Yield Prediction Using Weather Condition | Published in the 2024 International Conference on Advancement in Renewable Energy an d Intelligent Systems (AREIS), IEEE. | Forest (RF) The model uses Decisi on Tree | The mod el considers real- time environmental parameters for crop prediction, including: Temperature Humidity Soil | Random Forest performed better tha n Decision Tree in terms of accuracy and precision. The crop prediction accuracy reached approximately 98% using RF. | Overfitting in Decision Trees: The e use of multiple decision trees led to overfitting, which was resolved |

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|--|---------|---------|---------------------------------------|----------|--------------|
| | Forest | (DT-RF) | Rainfall | | using Random |
| | to | improve | | | Forest. |
| | accurac | ey and | | | Dependency |
| | | reduc | | | |
| | e overf | itting. | | | |
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| | | | | | | | | | for |
| | | | | | | | | | accurat |
| | | | | | | | | | e predictions, |
| | | | | | | | | | making it |
| | | | | | | | | | reliant on IoT systems. |
| 3 | A | Publi | shed in | The stu | ıdy | T | he model | AdaBoost | AdaBoost has |
| | Machin | the | | uses tw | 0 | cc | onsiders two | achieved | lower accuracy |
| | e Learning- | | Sixt | | machi | se | ets | 82% | (82%) |
| | based | h | | ne learr | ing | | 0 | accuracy in | compared |
| | Approach for | Intern | national | algorith | ms: | f | | crop yield | to |
| | Crop | Confe | erence | AdaBoo | ost | pa | arameters: | predictio | other |
| | Yield | on Tr | ends in | 11.7 | (for | F | or Crop | n. Random | boosti |
| | Prediction | Electi | ronics | crop | | | Yield | Forest | ng algorithms |
| | and Fertilizer | and | | 1 | yield | Pı | rediction: | had a | like |
| | Recommendat | Inform | matics | predicti | on) | St | tate | 95% | Gradient |
| | ion | (ICOI | EI) | Randon | n | | Distri | accuracy | Boosting. |
| | | 2022, | IEEE. | | Fore | ct | | i | Random Forest |
| | | -1 | | st (RF) | (for | S | eason Crop | n fe <mark>rtilizer</mark> | requir |
| | | · · | | fertilize | er | ty | | recommendatio | es large |
| | 4.00 | | | recomn | nendatio | | | n. | datasets and |
| | | | | n) | | a | Production | //_1 | may not |
| | | | | | | | | /. 0 | generalize well |
| | | 7 | | | | | | C.33 | to |
| | | | | | | | / | | different soil |

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| Ī | 4 | \mathcal{C} | Published in | The study | The | The Random | | |
| | | Crop | the 2023 3rd | utilizes three | mod | Forest classifier | | |
| | | Recommendatio | | | el considers | provided the | : The | |
| | | n System | Conference | ne learning | several | highest | accuracy of | |
| | | | on | algorithms: | parameters | accuracy in | predictions | |
| | | | Intelligent | Random | to | cro | depends on | |
| | | | Technologi | Forest | recommend | p | the quality | |
| | | | es (CONIT), | Support | suitable | recommendatio | and | |
| | | | IEEE. | | crops: Soil | n. The | availability of | |
| | | | | | Туре | system | soil and | |
| | | | | (SVM) | Rainfall | successfully | climate data. | |
| | | | | Logistic | Temperature | suggests | Limited Crop | |
| | | | | Regression | Geographical | crops | Variety: The | |
| | | | | | Location | based on soil | study focused | |
| | | | | | Soil pH | and climate | on a limited | |
| | | | | | _ | conditions, | number of | |
| | | | | | | helping | crops, which | |
| | | | \ \ | | | farmers | may | |
| | | | | | | make | restrict | |
| | | | | | | inform | its | |
| | | | | | | ed decisions. | applicability in | |
| | | | | | | 2 | diverse | |
| | | | | _ | | | farmin | |
| | | | | | | | g conditions. | |
| Ī | 5 | An Efficient | Published in | The study | The model | Random | Data | |
| | | Crop Yield | EAI | applies | considers | Forest | Dependency: | |
| | | Prediction | Endorsed | various | agricultural | Regressor | The model relies on | |
| | | System Using | Transactions - | | | achieved | historical | |
| | | Machine | on | | | th | data | |
| | | Learning | | | | e | | |

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|---|-----------------|--------------|--|--|--|--|
| | | Internet | regression- | and | highest R ² score | |
| | | 0 | based | environmen | (0.98), RMSE | Kaggle |
| | | f Things | machine | tal | (0.45), | repository, |
| | | (2024) | learning | factors, | an | which may not |
| | | | models: | including: | d MAE | reflect real-time |
| | | | Linear | Crop Type | (0.1088). | conditions. |
| | | | Regression | Average | 98% of | Limited Cro |
| | | | Kernel | Temperatur e | the | Variety: Only |
| | | | Ridge | Averag | variability in | certain crops |
| | | | Regression | e Rainfall | crop yield | were |
| | | | (KRR) | Amount of | can | considered, |
| | | | Lasso | Pesticides | be | which may |
| | | | Regression | Used (in | explained by | affe |
| | | | Random | tonnes) | the selected | ct |
| | | | Forest | , | parameters. | generalization |
| | | | Regression | | r | to other |
| | | | K- | | | regions. |
| | | | Nearest | | | 8 |
| | | | Neighb ors | | | |
| | | 7 | (KNN) | | | |
| | | | Regression | | | |
| 6 | Crop Prediction | Published in | The study | The | Bayes Net | Data |
| | Model Using | Applied | applies 15 | mod | and Naïve | Dependency: |
| | Machine | Sciences | different | el considers | Bayes | The model |
| | Learning | (MDPI), | machine | multiple | outperformed | relies on |
| | Algorithms | 2023, | learning | - | other | historical |
| | | Volume 13, | algorithms, | and | models, | data |
| | | Article 9288 | with a focus on | environmental | achieving | from |
| | | | the best- | factors: | nearly 99.5% | Kaggle |
| | The same of | | performing | | accuracy. | , which may |
| | | | models: | Nitrogen | Random | not reflect |
| | | | Bayes Net | (N) | Forest | real- |
| | | | (Best accuracy: | ` ′ | and | time conditions |
| | | | 00.50% | · • | Hoeffdi | Computational |
| | | | 99.59%) | I(P), | 11061101 | |
| | | | Naïve | (P), Potassium (K) | | - |
| | | | · · · · · · · · · · · · · · · · · · · | Potassium (K) | ng | Complexity: |
| | | | Naïve | Potassium (K) Weather | ng Tree also | Complexity: Deep |
| | | | Naïve Baye | Potassium (K) Weather Parameters: | ng Tree also performed well, | Complexity: Deep learni |
| | | | Naïve Baye s Classifier | Potassium (K) Weather Parameters: Temperature, | ng Tree also performed well, with accuracy | Complexity: Deep learni ng |
| | | | Naïve Baye s Classifier (Accuracy: 99.46%) | Potassium (K) Weather Parameters: Temperature, Rainfall, | ng Tree also performed well, | Complexity: Deep learni ng models |
| | | | Naïve Baye s Classifier (Accuracy: 99.46%) Hoeffding Tree | Potassium (K) Weather Parameters: Temperature, Rainfall, Humidity Soil | ng Tree also performed well, with accuracy | Complexity: Deep learni ng models like |
| | | | Naïve Baye s Classifier (Accuracy: 99.46%) Hoeffding Tree (Accurac | Potassium (K) Weather Parameters: Temperature, Rainfall, Humidity Soil Condition: | ng Tree also performed well, with accuracy | Complexity: Deep learni ng models like Multilayer |
| | | | Naïve Baye s Classifier (Accuracy: 99.46%) Hoeffding Tree (Accurac y: 99.46%) | Potassium (K) Weather Parameters: Temperature, Rainfall, Humidity Soil Condition: pH value | ng Tree also performed well, with accuracy | Complexity: Deep learni ng models like Multilayer Perceptron |
| | | | Naïve Baye s Classifier (Accuracy: 99.46%) Hoeffding Tree (Accurac y: 99.46%) Random Forest | Potassium (K) Weather Parameters: Temperature, Rainfall, Humidity Soil Condition: pH value Crop Labels: | ng Tree also performed well, with accuracy | Complexity: Deep learni ng models like Multilayer Perceptron require |
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| | | | Naïve Baye s Classifier (Accuracy: 99.46%) Hoeffding Tree (Accurac y: 99.46%) Random Forest | Potassium (K) Weather Parameters: Temperature, Rainfall, Humidity Soil Condition: pH value Crop Labels: | ng Tree also performed well, with accuracy | Complexity: Deep learni ng models like Multilayer Perceptron require |

| 7 | | Published in | The study | The | Random Forest | Data |
|---|---------------|---------------|---------------------|--------------|---------------|-----------------|
| | Fertilizer | IEEE | applies | mode | and SVM | Dependency: |
| | Recommendatio | International | multiple | 1 considers | showed | The |
| | | Conference | machine | various soil | the | mode |
| | Applying | О | learning | and | highest | 1 |
| | Machine | n Emerging | algorithms, | environment | accuracy for | relies on |
| | | Research | including: | al | cro | historical data |
| | Classifiers | in | Logistic | | p | from Kaggle, |
| | | | Regression Naïve | | prediction. | |

| | | Computation | Bayes Random | noromotore | Naïve Bayes | which may |
|---|---------------|-----------------------|-------------------|---------------------------|----------------|-------------------|
| | | al Science | Forest Decision | - | | |
| | | | | _ | | not always be |
| | | (ICERCS'23 | Tree Support | | Tree | up-to- date. |
| | _ |) | Vector | Nutrients: | performed well | |
| | | | Machine | Nitrogen | for | Time |
| | | | (SVM) | (N), | fertiliz | Integration: |
| | | ١ ١ | | Phosphorus | er | The system |
| | | | | (P), | recommendatio | does not |
| | | | | Potassium | n. | ye |
| | | | | (K) | | t |
| | | A . | | Weather | 3 | incorporate |
| | | | | Parameters: | | real- time |
| | | | | T <mark>empe</mark> ratur | | weather or soil |
| | | | | e, Rainfall, | | sensor data. |
| | 0.00 | | | Humidity ' | | |
| 8 | Crop | Published in | The | The | XGBoost | Data Quality |
| | Recommendati | 14th IEEE | stud | mode | achieved the | and |
| | on Based on | International | y applies | 1 considers | highest | Availability: |
| | Soil | Conference | multiple | various soil | accuracy | The model |
| | Properties: | 0 | machine | and | (99.32%) | relies on |
| | A | n Computing, | learning | environment | among | historical soil |
| | Comprehensive | Communicatio | algorithms, | al | | test data from |
| | Analysis | n, and | including: | | l models | Kaggle, which |
| | T Indi y 515 | Networking Networking | Decision Decision | including: | tested. | may not always |
| | | Technologies | Tree | Soil Soil | | be up-to-date. |
| | | (ICCCNT), | (Accuracy: | Nutrients: | and Random | |
| | 1 | 2023 | 90%) | Nitrogen (N), | | Generalization |
| | B / A A A | 2023 | Naïve | Phosphorus | performed well | |
| | | | Bayes | (P), | with over 99% | Cro |
| | | | - | Potassium | | |
| | | | (Accuracy: | | accuracy. | p manamandatia |
| | | | 99.09%) | (K) | | recommendatio |
| | | | Support | Weather | * | ns may |
| | | | Vector | Parameters: | | not |
| | | | Machine | Temperature, | | generalize well |
| | | | (SVM) | Humidity, | | to regions |
| | | | (Accuracy: | Rainfall | | wit |

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|-----|--------------|-----------------------|----------------|-------------------|-------------------|-----------------------|
| | | | 10.68%) | | | h |
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| 9 | Crop | Published in | The study uses | The | The Ensemble | High |
| | Recommendati | 2022 | an | model | Model | Computational |
| | on System | International | ensemb | considers | outperformed | Cost: |
| | Usin | Conference Conference | le learning | various soil | individual | Th |
| | g Ensembling | on | approach, | and climate | algorithms | e ensemble |
| | Technique" | Breakthrough | combining | paramete | i | approach |
| | | in Heuristics | multiple | rs, | n terms of | requires more |
| | | An | machine | including | accuracy and | computational |
| | | d | learning | : | reliability. | power |
| | | Reciprocation | models | | Random | tha |
| | | of Advanced | for | Soil | Forest | n individual |
| | | Technologies | better | Nutrients: | and | models. |
| | | (BHARAT), | accuracy: | Nitrogen | | Lack of Real- |
| | | IEEE | Random | 2 122 2 8 2 2 2 | nt Boosting | Time |
| | | | Forest | | models | Integration: |
| | | | Support | | contributed | The model is |
| | | | Vector | | the | trained |
| | | | Machine | | most to | |
| | | | | | improving | 0 |
| | | | (SVM) Logistic | | | n historical data, |
| | | | Regression | | prediction | |
| | | | Naïve Bayes | | performance. | which may |
| | | | Gradie | | | not |
| | | | nt December | | | |
| | | | Boosting | | | |

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|--------|--|--|--|--|---|---|
| ww.ije | ert.org | | © 2025 IJCR | (N), Phosphorus (P), Potassium (K) Weather Parameters: Temperatur | ssue 4 April 2025 | always be upto-date. |
| | | | | e, Humidity, Rainfall Soil pH Level Moisture Content Previous Crop | | |
| 10 | Crop Recommendati on Based on Soil Properties: | Published in 14th IEEE International Conference o n Computing, | The study applies multip le machine learning | Grown The mode I considers various soil and environment | XGBoost achieved the highest accuracy (99.32%) | Data Quality and Availability: The mode |
| | Comprehensive Analysis | Communication, and Networking Technologies (ICCCNT), 2023 | algorithms, including: Decision Tree (Accuracy: 90%) Naïve Baye s (Accuracy: 99.09%) Support Vect or Machine | al parameters, including: Soil Nutrients: Nitrogen (N), Phosphorus (P), Potassium (K) Weather Parameters: Temperatur | among all models tested. Naïve Bayes and Random Forest also performe d well with over 99% accuracy. | Generalization Issues: Cro p |
| 11 | Crop | This paper | (SVM) The study | e, Humidity, Rainfall | Decision | recommendati ons may not generalize well to regions wit h different soil properties. Dataset |

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|--|--|--|--|--|---|
| Recommendatio n System usin g Machine Learning | appears to be from an academic conference but does not have an IEEE DOI. It was presented at Devang Patel | applies fou r supervised machine learning algorithms for crop recommendatio n : Decision Tree (DT) Support Vector Machine (SVM) Logistic | dataset considers the following soil and climate factors: Soil Nutrients: Nitrogen (N), | performed best, achieving 99.5% training accuracy and | Limitation: The syste m relies on historical data from Kaggle, which may not reflect real-time agricultural conditions. |
| | Institute of Advance Technolog | Regression (LR) Gaussian Naïve Bayes (GNB) | Phosphorus (P), Potassium | | No Real- Time Data |

| | Institut | e of | Regression | Pł | nosphorus | accura | cy. | No | Real- |
|--|----------|------|------------------------|----|--------------|--|------------|-----------|--------|
| | Advan | ce | (LŘ) Gaussian Naïve | (P |), | Soil | nutrients | Time | |
| | Techno | olog | Bayes (GNB) | Po | otassium | (NPK) | and pH | | Data |
| | У | | Buyes (GIVB) | (K | (2) | levels | are the | Integrat | ion: |
| | | an | | W | eather | most s | ignificant | The | |
| | d | | ₹) | C | onditions | factors | s in crop | 1 | mode |
| | Resear | ch, | | : | | sele <mark>cti</mark> | on. | 1 | |
| | CHAR | US | | Τe | emperatu | | | does | |
| | AT, | | | re | , | | | ď | no |
| | India. | | | H | umidity, | | | t incorp | orate |
| | | | | | ainfall | and the same of th | $\sim 3\%$ | live we | eather |
| | | | | Sc | oil pH Value | | 13.00 | or soil s | sensor |
| | | | | | | | | data | |

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|----|-------|------------------|-----------------------------|------|---------------|-------------------|---------------------|---------------------------|--|
| | 12 | Crop | Published in | n | The | study | The dataset | Naïve Bayes | Data |
| | | Recommenda | 2023 | | applies | _ | considers | achieved the | Dependency |
| | | tio n Using | Internationa | 1 | | thre | the | highest | : The model |
| | | Machine | Conference | | e machine | | following | accuracy | relies |
| | | Learning | on | | learning | | soil | (99.09%), | on |
| | | | Data | | algorithms | | and | 1 0 | historical soil |
| | | | Sci | enc | | for | clima | Random Forest | an |
| | | | e | | crop | | te parameters: | | d weather |
| | | | and | | recommenda | atio | Soil Nutrients: | Soil | data, which |
| | | | Netv | VO | n | | Nitrogen | | may |
| | | | rk Security | | : | | (N), | s (NPK) | not |
| | | | (ICDSNS), | | Support Ve | | | and | always be up |
| | | | IEEE | | Machine | | | humidity were | to date. |
| | | | 4 N | | (SVM) | | ` ' | | Lack of Real- |
| | | | | | Random Fo | | Weather Conditions: | * | Time Integration: |
| | | | | | Naïve Bayes | 8 | Conditions: | nt parameters influencing | No real-time |
| | | | | | | | Temperatur | _ | IoT |
| | | | | | | | e, Humidity, | crop selection. | senso |
| | | | | | 1 | | Rainfall | selection. | r |
| | | | | | | | Soil pH Level | | data is |
| | | | _ | | | | Bon pri Lever | 3 | incorporated |
| | | | | | = | | | | for |
| | | | | | | | | | dynam |
| | | | | | | | | | ic updates. |
| | 13 | Crop Yield | Published | in | The st | udy | The dataset | Deep | High |
| | | | | | | | | Neura | Computationa |
| | | Prediction using | 2021 F | ifth | applies seve | eral | considers | Network | I Cost: |
| | 1 | Machine | <mark>Intern</mark> ationa | 1 | machine | | multiple | (DNN) | Deep |
| | | 0 | Conference Conference | | learning | | agricultural | | learning |
| | | Algorithm | | 0 | _ | | and | most accurate | models |
| | | | <mark>n Inte</mark> lligent | | d deep | | environme | results for crop | |
| | | | Computing 1 | | learning | | ntal | yield | and DNN |
| | | | and Control | | algorithms f | | parameters, | prediction. CNN and | |
| | | | Systems | | crop | | including: | | require |
| | | | (ICICCS), | | | iel | | | significant |
| | | | IEEE | | d prediction: | | | able to capture | computational |
| | | | | | | | | non- | Data |
| | | | | | | | | linear | Dependency: |
| | | | | | Artificial | | Soil | relationships | The model |
| | | | | | Neural | | Features: | between input | relies on |
| | | | | | Network | | Soil | parameters and | historical data |
| | | | | | (ANN) | | type | yield. | and the state of t |
| | | | | | Comv. 14! | 1 | , soil maps, | | |
| | | | | | Convolution | | and soil | | |
| | | | | | Neural | | nutrient | | |

| | a Maahina | 2024 1 | st | applies | co | onsiders | performed | Dependency |
|----|--------------------|---------|----------|-------------------|-----|----------------|--|-----------------|
| | Macilile | Interna | | sever | | ultiple | best | : The model |
| | Learning-Based | Confe | rence | al machine | | gricultural | | relies |
| | • | | 0 | learning | | nd | accuracy), | on |
| | Optimizing Crop | n Adva | | algorithms | | nvironme | • / / | historical soil |
| | Recommendatio | | in | for | | al | Random | an |
| | | Comp | | crop | | arameters, | | d weather |
| | | _ | _ | recommendatio | - | cluding: Soil | | data, which |
| | | n and | anneun o | n | | haracteristi | | may |
| | | Netwo | rking | | cs | | syste | not |
| | | (ICAC | _ | Decision Tree | : | | The second secon | always be up |
| | | IEEE | , | Classifier | ľ | Nitroge | - | to date. |
| | | | | Random | n | (N), | L. Committee of the com | Lack of Real- |
| | | | | Forest | | hosphorus | | Time |
| | | | | Classifier | | P), | | Integration: No |
| | | | | Naïve Bayes | | otassium | | real-time IoT |
| | | | | Classifi | | ζ), | | sensor data is |
| | | | | er Support | (1 | p | | incorporated |
| | | | | Vector Machine | Н | | | for dynamic |
| | | A | | v cetor iviaenine | | vel | 3 | updates. |
| | | | | (SVM) | 1 | /eather | | apaates. |
| | | | | K-Nearest | | onditions: | | |
| | | | | Neighbors | | emperatur | | |
| | | | | (KNN) | | Humidity, | | p. |
| | | | | (IKI VI V) | | ainfall | | |
| | | | | | | rop Yield | / 8 | - |
| | | | | | D | ata | | |
| 15 | | Publis | | The study | | he dataset | Random | Data |
| | - | | 2024 | applies | No. | onsiders | | Dependency: |
| | Recommenda | Interna | ition | thre | m | ultiple | | The system |
| | tio n using | al | | e machine | ag | gricultural | highest | relies on |
| | Machine | Confe | rence | learning | ar | nd | accuracy | historical |
| | Learnin | | 0 | algorithms | er | nvironmental | (99%), | datasets from |
| | | n Auto | mation | for | | arameters, | making it the | Kaggl |
| | | and | | crop | in | cluding: | | e, which may |
| | | Comp | utation | recommendatio | S | oil Nutrients: | | not reflect |
| | | (AUT | OCOM), | n | N | itrogen | recommendati | curren |
| | | IEEE | | : | | (N) | | t conditions. |

| Random Forest | , Phosphorus | Tree and | Limited |
|----------------|---------------|--------------|-----------------|
| | - | Logistic | |
| (RF) - Best | (P), | • | Cro |
| performer | Potassium (K) | Regression | p Variety: Only |
| (99 | Weather | also | 11 crops |
| % accuracy) | Conditions: | performed | were |
| Decision | Temperatur | well, but RF | considered, |
| Tree | e, | was superior | limiting |
| (DT) - 98% | Humidity, | in terms of | its |
| accuracy | Rainfall | precision. | adaptability to |
| Logistic | Soil pH Level | | diverse farming |
| Regression | | | conditions. |
| (LR) | | | |
| - 95% accuracy | | | |

| 16 | IoT Based | Publish | ed in | The | The dataset | Random Forest | High |
|----|---------------|----------|----------|--------------------------|---------------|-----------------|-----------------|
| | Smart Soil | 2023 | | study | considers | Regression | Computational |
| | Fertiliz | Internat | ional | applies | multiple soil | achieved | Complexity: |
| | er Monitoring | Confere | ence | multiple | an | the | The XGBoost |
| | and | | on | machine | d | highest | model requires |
| | ML Based | Electric | al, | learning | environment | accuracy | |
| | Crop | Compu | ter | algorit <mark>hms</mark> | al | (99.09%), | more |
| | Recommendati | | an | for | parameters, | making it the | processing |
| | on System | d | | crop | including: | best- | power than |
| | | Commu | inicatio | recommendatio | Soil | performing | simpl |
| | | n Engin | eering | n: Linear | Nutrients: | model. | er models. |
| | | (ECCE |), IEEE | Regression | Nitrogen (N), | XGBoost also | Limited Crop |
| | | | | (LR) | Phosphorus | performed well, | Variety: Only |
| | D (P. 4 | | | Rando | (P), | with 98.63% | 22 crops |
| 1 | A | | | m Forest | Potassium | accuracy. | wer |
| | | | | Regression | (K) Weather | | e considered in |
| | | | | (RFR) | Conditions: | 10 | the dataset. |
| | | | | Decision Tree | Temperatur | | |
| | | | | (DT) | e, Humidity, | | |
| | | | | XGBoost | Rainfall | | |
| | | | | | Soil pH Level | | |

| ww.i | jcrt.org | | | © 2025 | IJCR | Ti volume 13, i | ssue 4 April 2025 | 155N: 2320-2882 |
|------|-----------------------|-----------|-------|--------------|------|-------------------|-------------------|-------------------------------|
| 17 | Optimizing | Publishe | ed in | The | | The model | CRST | Complexity in |
| | Crop | 2025 | | stuc | ly | considers | outperformed | |
| | Recommendati | Internati | onal | introduces a | • | multiple soil | * | Setting |
| | on System | Confere | | Threshold- | | an | Forest | Thresholds: |
| | Usin | | | Based | | d | and | The |
| | g | Multi-A | | Cro | n | environment | Decisio | syste |
| | Threshold | Systems | _ | Recommend | - | al | | m requires |
| | an | Systems | | ion | ·ut | parameters, | | extensive data |
| | d Decision- | r Collab | | Sys | te | including: | ng 90% | analysis to |
| | Level Fusion" | Intellige | | m (CRST), | i.c | Soil | accuracy. | set |
| | Level I distoit | (ICMSC | | which | | Nutrients: | • | accurate |
| | | IEEE | .1), | integrates: | | Nitrogen (N), | | thresholds. |
| | | | | Rule-Based | | Phosphorus | 1 | Limited |
| | | | | Decision | | (P), | prediction | Cro |
| | | | | Fusion | | Potassium | accuracy, | |
| | | | | Ordinary Le | act | (K) Weather | • | P Variety: The |
| | | | | Squares (OI | | Conditions: | making the | model currently |
| | | | | Regression | رد. | Temperatur | | focuses |
| | | | | Regression | | | real- world use. | |
| | | | | | | e, Humidity, | rear- world use. | 0 n specifie |
| | | | | | | Rainfall | | n specific |
| 10 | Performance | Publishe | 1 | The | | | Dandon | seasonal crops. No Real-Time |
| 18 | Evaluation Evaluation | in 2023 | e u | | atud | | Random Forest | Data: The |
| | | 17th | | | stud | | achieved the | |
| | | | | y evaluates | | | | system relies on |
| | f Machine | Internati | OII | several | | samples, later | | historical data |
| | Learning | al | | machine | | augmented to | | from Kaggle, |
| | | Confere | | learning | | 6000 and | (99.52%), | which may not |
| | a Cluster-based | g. 1 | | algorithms | C | 12000 | making it the | reflect current |
| | Crop | n Signal | | | for | | best- | conditions. |
| | Recommendati | Image | | crop | . \ | includes: Soil | 1.3 | Limited Crop |
| | on System" | Technol | | recommend | atio | Nutrients: | * | Variety: Only |
| | | т , | & | | | | | 22 |
| | | Internet- | Based | Random For | rest | | | |
| | | G . | | (RF) - Best | | DT'. | c · | |
| | | Systems | | performe | | Nitrogen | performing | crop types were |
| | | (SITIS), | IEEE | (00.520/ | | (N) | | included in the |
| | | | | (99.52% | | , Phosphorus | XGBoost, | dataset |
| | | | | accuracy) | | (P), | LGBM, | |
| | | | | XGBoost | | Potassium | an | |
| | | | | 00.400/ | - | (K) | d Gradient | |
| | | | | 99.48% | | Weath | Boosting | |
| | | | | accuracy | | er Conditions: | models showed | |
| | | | | Decision | _ | Temperature, | _ | |
| | | | | (D-T) | Tre | Humidity, | close | |
| | | | | e (DT) - | | Rainfall | results to | |
| | | | | 99.03% | | Soil pH Level | RF. | |
| | | | | accuracy | | | Increasing | |

| /WW | /.ijC | crt.org | | | © 2025 IJCR | I Volume 13, Is | ssue 4 April 2025 | ISSN: 2320-2882 |
|-----|-------|--|----------|--------|-----------------|---------------------------|-----------------------------|-----------------|
| | | | | | K | | dataset size did | |
| | | | | | - Nearest | | not | |
| | | | | | Neighbors | | significantly | |
| | | | | | (KNN) | | affect | |
| | | | | | | | model | |
| | | | | | - 98.00% | | accuracy, | |
| | | | | | accuracy | | indicating a | |
| | | | | | | | stable | |
| | | | | | | | system. | |
| | | | | | | | | |
| | | | | | | | | |
| | | | | | | | | |
| L | | D 1 = | D 1 11 1 | | mi i | | D 1 D | N. D. 1 =: |
| 1 | 9 | | Publish | ed in | The study | The dataset | Random Forest | |
| | | Sampling for | 2023 | | applies | includes | | Data |
| | | Crop | Internat | | multiple | multiple | highest | Integration: |
| | | Recommendat | Confere | | machine | agricultural | accuracy, | The system |
| | | ion Based on | | 0 | learning | and | making it the | |
| | | Ambient | n Advar | | techniques | environment | best model for | historic |
| | | Climate | Comput | _ | for | al | crop | al datasets, |
| | | an | Technol | logies | crop | parameters, | recommendatio recommendatio | which |
| | | d Soil | and | | recommendati | such as: | ns | may not |
| | | Conditions | Applica | | on: Random | Soil | | reflect current |
| | | | (ICACT | (A), | Forest (RF) - | Nutrients: | Linea | conditions. |
| | | | IEEE | | Best | Nitrogen | r | Limited Crop |
| | | | | | performer | (N), | Regression | Variety: Only |
| | | | | | K- Nearest | Phosphorus | | 22 crops |
| | | P (P) 4 | | | Neighbo | (P), | used for | wer |
| | | The state of the s | | | _ | Potassium | rainfall | e included in |
| | | | , * · | | rs (KNN) | (K) Weather | prediction, | the dataset. |
| | | | | | Decision | Conditions: | achieving | |
| | | | | | Tree | Temperatur | 91 | |
| | | | | | (DT) | e, Humidity, | % accuracy. | |
| | | | _ | | Linear | Rainfall Soil pH Level | | |
| | | | | | Regression (for | Son pri Level | | |
| | | | | | rainf | | | |
| | | | | | all prediction) | | | |
| | | | | | an prediction) | | | |

| 20 | Crop | This | K-Nearest | Nitrogen | Random Forest | The dataset |
|----|------------|----------------|-----------------|---------------|------------------|------------------|
| | Prediction | paper | Neighbor | (N), | Classifi | used was |
| | Using | was | (KNN) | Phosphorus | er with both | limited, which |
| | Machine | published in | Decision | (P), | Entropy and | might not |
| | Learning | the | Tree | an | Gini Criterion | generalize well |
| | | Journal | Classifier | d | provided | for all regions. |
| | | of | (Entropy and | Potassium | the | Only a few |
| | | Physics | Gini Criterion) | (K) content | highest | machine |
| | | : Conference | Random | in soil | accuracy of | learning |
| | | Series 2161 | Fore | Temperature | 99.32%. | algorithms |
| | | (2022) | st Classifier | (°C) | Decision Tree | were |
| | | 012033, under | (Entropy and | Relative | Classifier using | compared; deep |
| | | the conference | Gini Criterion) | Humidity | Gini Criterion | learning |
| | | AICECS | · | (%) | showed 98.86% | models like |
| | | 2021. | | pH value of | accuracy, | CNN or ANN |
| | | | | soil Rainfall | slightly better | were not tested. |
| | | | | (mm) | than | |
| | | | | | Entropy | |
| | | | | | Criterion. | |

| 2 | 21 | Soil-Based | Published in | Decision | Soil | The proposed | Relies on |
|---|----|-------------|--------------------|--------------|--------------|----------------|-----------------|
| | | Crop | the 2024 | Trees Random | Parameters: | Soil-Based | accurate soil |
| | | Recommendat | International | Forest | pH level | Crop | data collection |
| | | ion | Conference | Gradient | Nitrog | Recommendati / | for |
| | | Syste | 0 | Boosting | en (ppm) | on System | effectiveness. |
| | | m Using | n Advances | (XGBoost or | Phosphorus | (SBCRS) | Possible bias |
| | | Machine | in | LightGBM) | (ppm) | outperformed • | in historical |
| | | Learning | Data | | Potassium | existing | cro |
| | | | Engineering | | (ppm) | systems. | p performance |
| | | 1 | and Intelligent | | Soil texture | Performance | data, affecting |
| | | | Computing | 1 | | Metrics: | recommendatio |
| | | | Systems | | | Accuracy: | ns |
| | | | (ADICS) | | | 93% | |
| | | | | | | (vs. 78% in | |
| | | | | | | the existing | |
| | | | | | | syste | |
| | | | | | | m) Precision: | |
| | | | | | | 89% | |
| | | | | | | (vs. 72%) | |
| | | | | | | Recall: | |
| | | | | | | 93 | |
| | | | | | | % (vs.81%) | |
| | | | | | | F1 Score: 90%. | |

III. PROPOSED SYSTEM

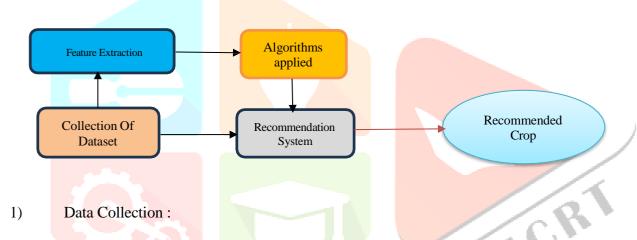
Fig 1: Block Diagram of Overall Methodology of Proposed System

In our framework, we have proposed a procedure that is separated into various stages as appeared in Figure 1. The five phases are as per the following: The five phases are as per the following:

- 1) Collection of Datasets
- 2) Pre-processing (Noise Removal)
- 3) Feature Extraction
- 4) Applied Machine Learning Algorithm
- 5) Recommendation System
- 6) Recommended Crop

Flow of the Proposed System

As demonstrated in the figure, the methodology to extract the sentiment contains the several steps that are described below:



The dataset consists of parameters like Nitrogen (N), Phosphorous (P), Potassium (K), PH value of soil, Humidity, Temperature and Rainfall. The datasets have been obtained from the Kaggle website. The data set has 2200 instance or data that have taken from the past historic data. This dataset include twenty two different crops such as rice, maize, chickpea, kidneybeans, pigeonpeas, mothbeans, mungbean, blackgram, lentil, pomegranate, banana, mango, grapes, watermelon, muskmelon, apple, orange, papaya, coconut, cotton, jute, and coffee.

Dataset - Link: https://www.kaggle.com/datasets/atharvaingle/crop- recommendation-dataset

2) Noise Removal:

For the successful application pre-processing is required. The data which is acquired from different resources are sometime in raw form. It may contain some incomplete, redundant, inconsistent data. Therefore in this step such redundant data should be filtered. Data should be normalized.

3) Feature Extraction:

This step is focus on identifying and using most relevant attribute from the dataset. Through this process irrelevant and redundant information is removed for the application of classifiers.

4) Methodology:

In this proposed system applied different Machine Learning algorithms like Decision Tree, Support Vector Machine (SVM), Random Forest, and K- nearest neighbor (KNN).

A) Decision Tree;

Decision tree classifiers utilize greedy methodology. It is a supervised learning algorithm where attributes and class labels are represented using a tree. The main purpose of using Decision Tree is to form a training prototype which we can use to foresee class or value of target variables by learning decision rules deduced from previous data (training data). The Decision tree can be described by two distinct types, namely decision nodes and leaves. The leaves are the results or the final end results. Each node in the tree acts as a test case for some attribute, and each edge descending from that node corresponds to one of the possible answers to the test case.

We have applied Decision tree approach in our model as:

- i) Importing library DecisionTreeClassifier
- ii) Now we create DecisionTree Classifier object
- iii) In the last we fit our data

from sklearn.tree Class.

B.)Support Vector Machine (SVM):

Support Vector Machine (SVM) is a supervised machine learning algorithm or model which can be utilized for classification and as well as for regression challenges. However, we mainly use it in classification challenges. SVM is generally represented as training data points in space which is divided into groups by intelligible gap which is as far as possible. In SVM algorithm, each data item is plotted as a point in n-dimensional space with each feature value being the value of a specific coordinate. Then the classification is performed by finding the hyper-plane differentiating the two classes.

C) KNN:

The K-Nearest Neighbors (KNN) algorithm in a crop recommendation system works by analyzing historical agricultural data, such as soil type, rainfall, temperature, and past crop yields.

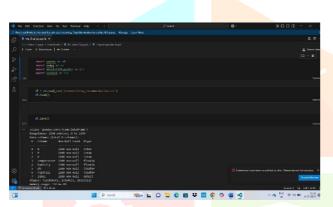
The system gathers data on soil properties, climate conditions, and crop performance Relevant features like nitrogen, phosphorus, potassium (NPK) levels, pH, temperature, and humidity are chosen. The algorithm checks which crops were successfully grown in the K nearest neighbors and recommends the most frequently occurring crop.

D) Random Forest:

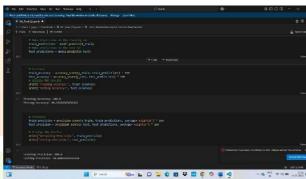
Random Forest, a machine learning algorithm, is widely used in crop recommendation systems due to its accuracy and robustness. 1. he system gathers data on soil properties, weather conditions, crop yield history, and other relevant factors. Important features such as soil pH, temperature, rainfall, and nutrient levels are selected. 3. Multiple decision trees are created using different subsets of the data. Each tree makes an independent prediction. The final crop recommendation is determined by aggregating the predictions from all trees, selecting the most frequently suggested crop.

IV. RESULT AND ANALYSIS

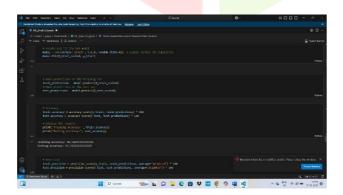
Dataset –



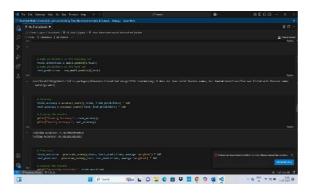
<u>Decision Tree</u> –



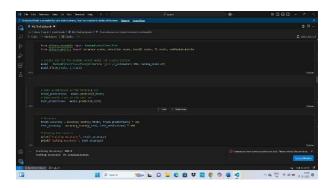
Support Vector Machine (SVM) –



<u>KNN</u> –



Random Forest -



| Algorithms | Accuracy | Recall | Precision | F1-score |
|------------------|---------------------------------|-------------------|-------------------|-------------------|
| Decision Tree | 98.636363636363 | 98.636363636363 | 98.680555555556 | 98.63152866630287 |
| SVM | 97.72727272727 <mark>273</mark> | 97.72727272727273 | 97.87326467724195 | 97.70616589588195 |
| KNN | 95.6818181818181 | 95.68181818181817 | 96.28976143584399 | 95.67492608232794 |
| Random Forest | 99.318181818181 | 99.31818181818181 | 99.37348484848485 | 99.31754816901672 |

V. CONCLUSION

We have developed and applied a smart system that can suggest suitable crops for farmers across India. This system would help the farmers choose the best crop based on factors like Nitrogen, Phosphorous, Potassium, PH Value, Humidity, Temperature, and Rainfall. By using this research we can increase productivity of the country and produce profit out of such a technique. This research can enhance the country's productivity and profitability by using this technique. This way, farmers can grow the right crop and increase their income and the country's overall earnings. We have evaluated machine learning algorithms and discovered that Decision Tree and Random had the best accuracy among them.

VI. FUTURE WORK

The system can be enhanced further to add following functionality:

- The main future work's aim is to improved dataset with larger number of attributes.
- We need to build a model, which can classify between healthy and diseased crop leaves and also if the crop has any disease, predict which disease is it.
- To build website and mobile app for easy to use.

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