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Crop Yield Prediction using Machine Learning

M. Venu
Electronics and communication Engineering
VNR Vignana Jyothi Institute of Engineering and Technology
Hyderabad, India

B B Shabarinath
Assistant Professor
Electronics And Communication Engineering
VNR Vignana Jyothi Institute of Engineering and Technology
Hyderabad, India

K Deepthi
Assistant Professor
Electronics and Communication Engineering
VNR Vignana Jyothi Institute of Engineering and Technology
Hyderabad, India

***Abstract*— Predicting crop yield based on environmental, soil, water, and crop parameters is a crucial research area. Traditional deep learning models often struggle to directly map raw data to crop yield values and depend heavily on the quality of feature extraction. To address these issues, our approach utilizes the K-Nearest Neighbors (KNN) algorithm. KNN predicts crop yield by identifying the 'k' most similar historical data points based on input parameters, thus maintaining the integrity of the original data distribution. After collecting and preprocessing relevant data, the KNN model is trained with historical instances of environmental and crop parameters and their corresponding yields. For new input data, KNN finds the closest 'k' neighbors and averages their yields to predict the crop yield. This straightforward approach avoids the complexities of feature extraction and model assumptions inherent in deep learning methods. Our KNN model achieves an impressive prediction accuracy of 93.7%, significantly outperforming many existing models by leveraging the simplicity and effectiveness of the KNN algorithm.**
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***Index Terms*— Deep Learning (DL), Machine Learning (ML), SVM, Epileptic Seizures**

I. INTRODUCTION

Agriculture is one amongst the substantial areas of interest to society since a large portion of food is produced by them. Currently, many countries still experience hunger because of the shortfall or absence of food with a growing population. Expanding food production is a compelling process to annihilate famine. Developing food security and declining hunger by 2030 are beneficial critical objectives for the United Nations. Hence crop protection; land assessment and crop yield prediction are of more considerable significance to global food production [1]. A country’s policymaker depends on precise forecast, to make appropriate export and import assessments to reinforce national food security. Cultivators and farmers further benefit from yield forecast to make financial and management decisions. Agricultural supervision, especially the observation of crop yield, is indispensable to determine food security in a region [2]. On the other hand, crop yield forecasting is exceedingly challenging because of various complex aspects. Crop yield mainly depends upon climatic conditions, soil quality, landscapes, pest infestations, water quality and availability, genotype, planning of harvest activity and so on [3]–[5]. The crop yield processes and strategies vary with time and they are profoundly non-linear in nature [6], and intricate due to the integration of a wide extent of correlated factors [7], [8] characterized and impacted by non-arbitrate runs and external aspects. Usually, a considerable part of the agricultural framework cannot be delineated in a fundamental stepwise calculation, especially with complex, incomplete, ambiguous and strident datasets. Currently, many studies demonstrate that machine learning algorithms have comparatively more improved potential than conventional statistics [9]–[12]. Machine learning belongs to the field of artificial intelligence by dint of which computers can be instructed without definite programming. These processes resolve non-linear or linear based agricultural frameworks with remarkable forecasting ability [13]. In Machine learning agricultural frameworks, the techniques are obtained from the learning process. These processes demand over train to perform a specific task. After the completion of the training process, the model makes presumptions to test the information. Further, machine learning resembles an umbrella that holds various significant strategies and methodologies. On observing the most prominent models in agriculture, we can see the utilization of artificial and deep neural networks [14]. Deep learning is a subgroup of machine learning that can determine outcomes from varying arrangements of raw data. Deep learning algorithms, for example, can develop a probability model by taking a decade of field data and providing insights about crop performance under various climatic conditions [15]. Data scientists utilize various machine learning algorithms to derive actionable insights from the available information. Another intriguing area of artificial intelligence is reinforcement learning [16]. These can be examined as an essential class of algorithms that can be utilized for streamlining logic for dynamic programming. Reinforcement learning is the preparation of machine learning models to make decision sequences [17]. The agent learns to accomplish an objective in an ambiguous, potentially complex environment. Based on the agent’s action, the environment rewards it. This scenario depicts the machine as the agent and its surroundings as the environment. In recent times advanced and progressive artificial intelligence technique named, deep reinforcement learning (DRL) is profound for intelligent decision making in various domains like energy management [18], robotics [19], healthcare [20], smart grid, game theory [21], [22], finance, computer vision [23], Natural Language Processing [24], Sentiment analysis [25] and so on with an extensive combination of reinforcement learning methods with deep learning models [26], [27]. This model has been efficient to resolve a wide extent of complicated decision-making tasks that were formerly beyond the bounds for the machine. As a result, it is a convincing model endorsed for developing intelligent agricultural frameworks. The characteristic models of deep reinforcement learning include deep successor network, multi-agent deep reinforcement learning and deep Q-network.

Scope of the Project:

The project aims to develop and deploy a crop yield prediction system using the K-Nearest Neighbors (KNN) algorithm. It involves collecting and preprocessing diverse agricultural data encompassing environmental, soil, water, and historical yield information. The focus lies on algorithm development, optimization, and integration into a user-friendly platform for real-time predictions. Evaluation metrics will validate prediction accuracy, and comprehensive documentation will facilitate communication with stakeholders. Future enhancements may include additional data integration and algorithmic refinements to ensure the system's adaptability and scalability in addressing agricultural challenges.

II. LITERATURE REVIEW

The literature survey provides a comprehensive overview of recent advancements and key research findings in the field of agricultural technology, specifically focusing on precision agriculture and crop yield prediction. In today's rapidly evolving agricultural landscape, technological innovations play a crucial role in enhancing productivity, sustainability, and food security. By synthesizing findings from a range of studies, this survey aims to shed light on the diverse methodologies, techniques, and approaches being employed to address the complex challenges facing modern agriculture.

S. Li et al. [1] present the INCOME system, a practical land monitoring solution for precision agriculture utilizing sensor networks. This system offers a means to effectively monitor land conditions and optimize agricultural processes, contributing to improved crop yield and resource management.

A. D. Jones et al. [2] explore the complexities of assessing food security, emphasizing the need for comprehensive metrics to accurately measure and address food insecurity issues. Their review provides valuable insights for policymakers and researchers working towards enhancing food security globally.

G. E. O. Ogutu et al. [3] tackle the challenge of maize yield prediction in East Africa using dynamic ensemble seasonal climate forecasts. By incorporating probabilistic forecasting methods, their study aims

to provide more accurate and timely predictions to support agricultural planning and decision-making in the region.
M. E. Holzman et al. [4] propose an early assessment method for crop yield prediction based on remotely sensed water stress and solar radiation data. This approach offers a novel way to monitor crop health and yield potential, enabling proactive management strategies to optimize productivity.
A. Singh et al. [5] discuss the application of machine learning techniques for high-throughput stress phenotyping in plants. By leveraging advanced data analytics, their work aims to improve our understanding of plant stress responses and facilitate the development of stress-tolerant crop varieties.
R. Whetton et al. [6] delve into the nonlinear relationships between soil properties and crop yields, employing parametric modeling techniques to better understand and predict crop performance. Their study highlights the importance of considering soil variability in agricultural decision-making processes.
Y. Cai et al. [7] present a high-performance classification system for field-level crop types using time-series Landsat data and machine learning algorithms. This system offers a scalable and efficient solution for crop type mapping, aiding in agricultural land management and resource allocation.

III. EXISTING METHODS:

Existing systems for crop yield prediction typically involve traditional statistical methods and machine learning algorithms like linear regression, decision trees, and support vector machines. These systems require considerable feature engineering and manual selection of relevant variables. However, they may not fully capture the complex interactions between environmental factors and crop yields. Additionally, they may struggle to adapt to changing environmental conditions and handle uncertainty inherent in agricultural systems. While some existing systems achieve reasonable accuracy under specific conditions, they often lack scalability and robustness required for widespread adoption and real-time decision-making in dynamic agricultural settings. The existing systems for crop yield prediction have several disadvantages. Firstly, they require manual feature engineering and selection, which is labor-intensive and prone to human error. Secondly, due to their reliance on manual processes, these systems may overlook crucial variables that could significantly impact yield predictions. Thirdly, they have a limited capability to capture the intricate relationships between various environmental factors and crop yields. Additionally, these systems lack adaptability to changing agricultural conditions, making them less effective in dynamic environments. They also struggle to handle the inherent uncertainty in agricultural systems, leading to less reliable predictions. Furthermore, scalability limitations hinder their widespread adoption and the ability to support real-time decision-making. Lastly, these traditional methods often perform suboptimally, especially in complex and rapidly changing agricultural contexts.

IV. PROPOSED SYSTEM

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The proposed system for crop yield prediction leverages the K-Nearest Neighbors (KNN) algorithm to overcome the limitations of traditional methods. This system collects and preprocesses data on various environmental, soil, water, and crop parameters to ensure quality and consistency. Using KNN, the model is trained with historical data, where it stores instances and their corresponding crop yields. For new input data, the KNN model identifies the most similar historical instances to make yield predictions based on these close neighbors. By relying on the inherent similarities in the data, this approach allows for accurate and efficient crop yield forecasting without the need for complex feature extraction or model assumptions.

Advantages of Proposed System

i. Utilizing KNN to leverage patterns in environmental, soil, water, and crop parameters.
ii. Minimizing the need for manual feature engineering by letting KNN autonomously identify relevant features from the data.
iii. Improving adaptability to changing environmental conditions by continuously updating predictions based on nearest neighbors.
iv. Enhancing scalability and robustness to handle diverse agricultural contexts and provide timely predictions. v. Addressing uncertainty inherent in agricultural systems through the flexibility of the KNN algorithm.

METHODOLOGY:

- Data COLLECTION:

In this stage data set is prepared which has temperature, humidity, potassium. Nitrogen, phosphorus, and along with labels 1 to 7 and crops details.

N	P	K	temperatu	humidity	ph	rainfall	label
90	42	43	20.87974	82.00274	6.502985	202.9355	rice
85	58	41	21.77046	80.31964	7.038096	226.6555	rice
60	55	44	23.00446	82.32076	7.840207	263.9642	rice
74	35	40	26.4911	80.15836	6.980401	242.864	rice
78	42	42	20.13017	81.60487	7.628473	262.7173	rice
69	37	42	23.05805	83.37012	7.073454	251.055	rice
69	55	38	22.70884	82.63941	5.700806	271.3249	rice
94	53	40	20.27774	82.89409	5.718627	241.9742	rice
89	54	38	24.51588	83.53522	6.685346	230.4462	rice
68	58	38	23.22397	83.03323	6.336254	221.2092	rice
91	53	40	26.52724	81.41754	5.386168	264.6149	rice
90	46	42	23.97898	81.45062	7.502834	250.0832	rice

Fig 1: Sample dataset

The sample dataset provided contains several features related to environmental and soil conditions, which are used to predict crop yields. Here's a detailed explanation of each column in the dataset:

N: The amount of nitrogen in the soil, measured in units that likely represent concentration (e.g., parts per million).

P: The amount of phosphorus in the soil, also measured in concentration units.

K: The amount of potassium in the soil, measured similarly in concentration units.

temperature: The temperature of the environment where the crops are being grown, measured in degrees Celsius.

humidity: The humidity level of the environment, given as a percentage.

ph: The pH level of the soil, which indicates its acidity or alkalinity.

rainfall: The amount of rainfall received, measured in millimeters.

label: The type of crop being grown; in this dataset, all entries are labeled as "rice."

Pre-processing:
In this stage data is collected from dataset and divided to testing and training and given input to algorithm and fit to algorithm.

- **Train-Test Split and Model FITTING:**

In this step dataset is split in to training and testing phase and training data is used to input to model and test set is used for calculating accuracy of the model.

- **User Module:**

In this stage user gives input of all features from website and get output as which crop is best and yield for each crop.

Algorithm used:

Algorithm Description: k-Nearest Neighbors is a simple, instance-based learning algorithm used for classification and regression tasks. It makes predictions based on the majority class or the average of the k nearest data points in the feature space.

The K-NN working can be explained on the basis of the below algorithm:

Step-1: Select the number K of the neighbors

Step-2: Calculate the Euclidean distance of K number of neighbors

Step-3: Take the K nearest neighbors as per the calculated Euclidean distance.

Step-4: Among these k neighbors, count the number of the data points in each category.

Step-5: Assign the new data points to that category for which the number of the neighbor is maximum.

Step-6: Our model is ready.

ARCHITECTURE:

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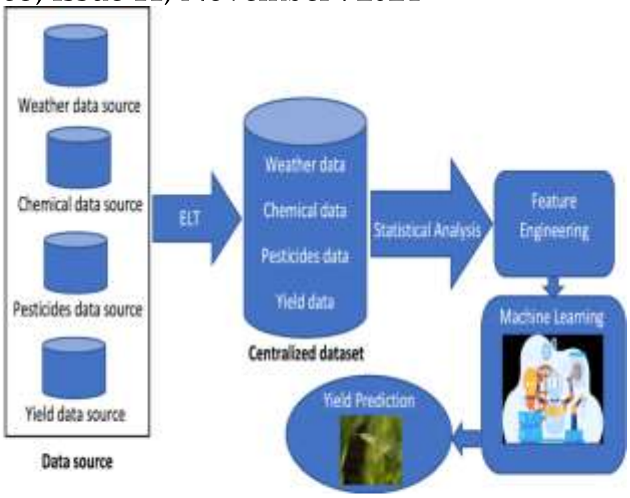

Figure 1. System Architecture

Steps to train the KNN model:

Training a k-Nearest Neighbors (**K**NN) classifier involves several steps.

Data Collection: Gather a dataset containing features and corresponding labels. Each data point should have a set of features and a label indicating its class or category.

Data Preprocessing: This step involves cleaning and formatting the data to make it suitable for training. Tasks may include handling missing values, scaling features, and encoding categorical variables.

Feature Selection/Extraction: Choose relevant features that are informative for the classification task. Sometimes, feature extraction techniques like PCA (Principal Component Analysis) or feature selection methods like information gain can be used to reduce the dimensionality of the data.

Splitting the Data: Divide the dataset into two subsets: a training set and a test set. The training set is used to train the model, while the test set is used to evaluate its performance. Common splits include 70-30 or 80-20 ratios.

Choosing k: Determine the value of k, the number of nearest neighbors to consider during classification. This can be done through techniques like cross-validation or by using domain knowledge.

Training the Model: In KNN, there is no explicit training phase as the model simply memorizes the training data. However, in practice, the training step may involve storing the training dataset or constructing data structures (like kd-trees) for efficient nearest neighbor search.

Distance Metric Selection: Choose an appropriate distance metric to measure the similarity between data points. Common choices include Euclidean distance, Manhattan distance, or cosine similarity.

Prediction: Given a new, unseen data point, the k-NN algorithm finds the k nearest neighbors from the training set based on the chosen distance metric. It then predicts the label for the new data point based on the majority class among its nearest neighbors.

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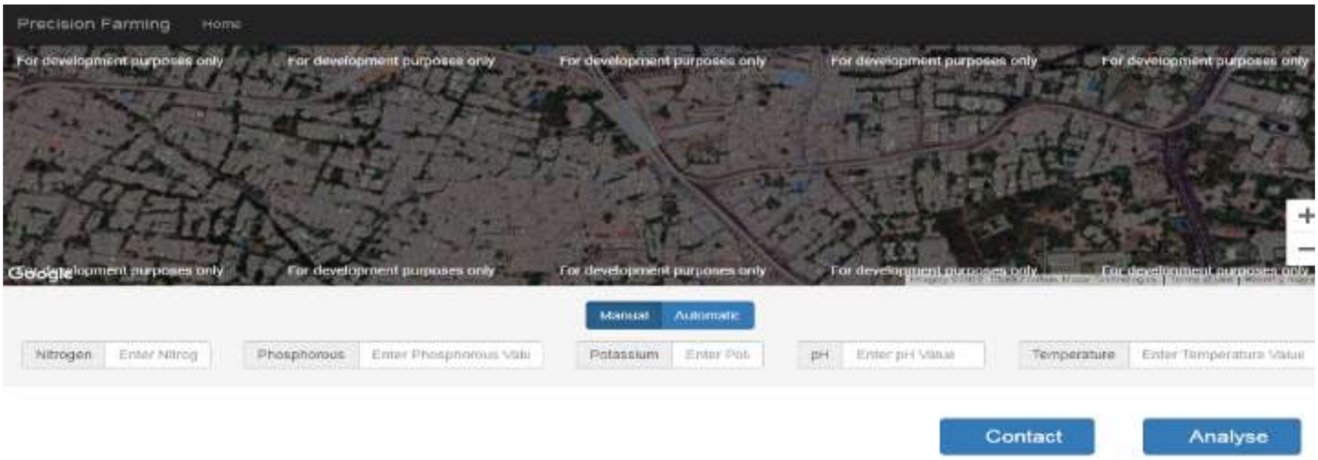
Model Evaluation: Evaluate the performance of the trained model using the test set. Common evaluation metrics for classification tasks include accuracy, precision, recall, F1-score, and ROC curves.

Parameter Tuning: Fine-tune the model parameters, such as the value of k or the choice of distance metric, to improve performance. This can be done using techniques like grid search or random search.

Deployment: Once the model is trained and evaluated satisfactorily, it can be deployed to make predictions on new, unseen data in real-world applications.

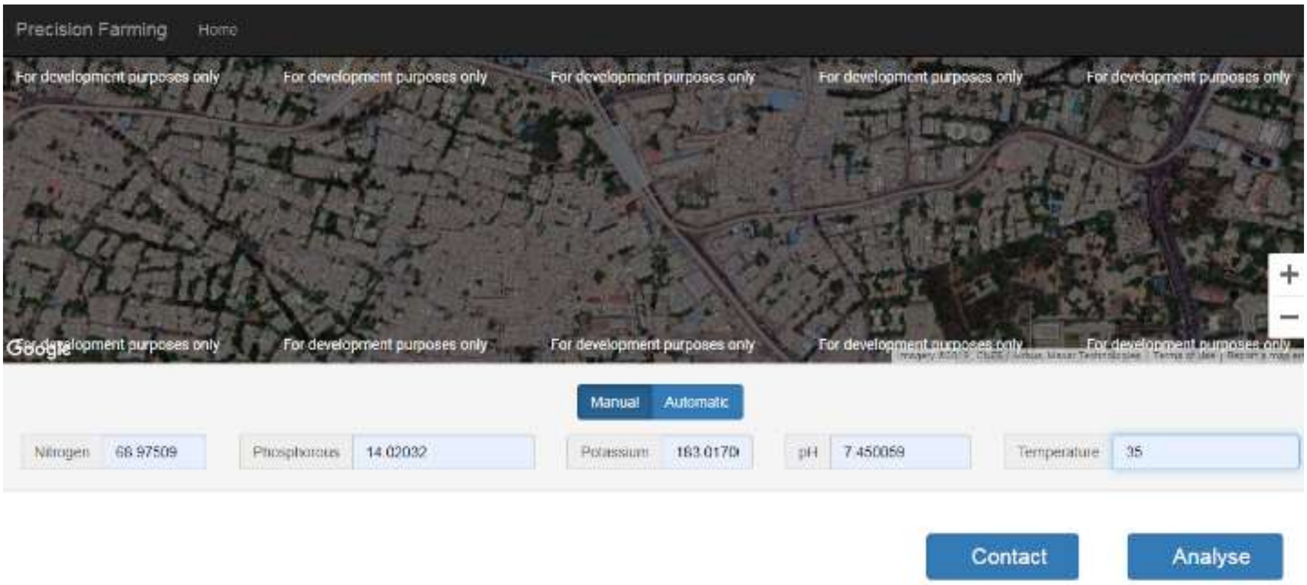
RESULTS:

DATASET:



State 1: idle

In this initial state, the system is on standby, awaiting user interaction or input.



State 2: give inputs using the user interface

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Give Inputs Using the User Interface - In this state, the user interacts with the system by providing necessary input parameters such as environmental, soil, water, and crop data through a user-friendly interface.

Precision Farming Home

Tomato Cultivation Guide Revenue/Hectare: Rs426000

Climatic Requirements

Tomato is a warm season crop, it requires warm and cool climate. The plants cannot withstand frost and high humidity. Also light intensity affects pigmentation, fruit colour, fruit set. The plant is highly affected by adverse climatic conditions. It requires different climatic range for seed germination, seedling growth, flower and fruit set, and fruit quality. Temperature below 10^{0}C and above 38^{0}C adversely affects plant tissues thereby slow down physiological activities. It thrives well in temperature 10^{0}C to 30^{0}C with optimum range of temperature is 21-24^{0}C. The mean temperature below 16^{0}C and above 27^{0}C are not desirable. The plant doesn't withstand frost, it requires low to medium rainfall, and does well under average monthly temperature of 21 to 23^{0}C. Avoid water stress and long dry period as it causes cracking of fruits. Bright sunshine at the time of fruit set helps to develop dark red coloured fruits.

Temperature Requirement

Sr. No.	Stages	Temperature (^{0}C)		
		Minimum	Suitable	Maximum
1.	Seed germination	11	16-29	34
2.	Seedling growth	18	21-24	32
3.	Fruit set (day)	10	15-17	30
	(night)	18	20-24	30
4.	Red colour development	10	20-24	30

Fertilizers

As the fruit production and quality depends upon nutrient availability and fertilizer application so balance fertilizer are applied as per requirement. The nitrogen in adequate quantity increases fruit quality, fruit size, color and taste. It also helps in increasing desirable acidic flavor. Adequate amount of potassium is also required for growth, yield and quality. Mono Ammonium Phosphate (MAP) may be used as a starter fertilizer to supply adequate phosphorus during germination and seedling stages. Calcium availability is also very important to control soil pH and nutrient availability. Sandy soils will require a higher rate of fertilizer, and more frequent applications of these fertilizers due to increased leaching of essential nutrients. The seedings are sprayed with starter solution of micronutrient. Before planting farm yard manure @ 50 ton per hectares should be incorporated. Normally tomato crop requires 120kg Nitrogen (N), 50kg Phosphorus (P_2O_5), and 50kg Potash (K_2O). Nitrogen should be given in split doses. Half nitrogen and full P_2O_5 is given at the time of transplanting and remaining nitrogen is given after 30 days and 60 days of transplanting.

Soil and tissue analyses should be taken throughout the growing and production season to insure essential nutrients are in their proper amounts and ratios. Tissue analysis of a nutritionally sufficient plant will show the following nutrient status.

	Nitrogen	Phosphorus	Potassium	Calcium	Magnesium	Sulphur
%	4.0-5.6	0.30-0.60	3.0-4.5	1.25-3.2	0.4-0.65	0.65-1.4
	ppm	Manganese	Iron	Boron	Copper	Zinc
		30-400	30-300	20-60	5-15	30-90

In the present situation it has been realized that the use of inorganic fertilizers should be integrated with renewable and environmental friendly organic fertilizers, crop residues and green manures.

State 3: get the guidelines for cultivation

Get the Guidelines for Cultivation - After processing the input data, the system transitions to this state where it provides guidelines for cultivation based on the predictions and analysis derived from the input parameters.

Here we can see all the data related to things we should take care of to grow the crop which best suited.

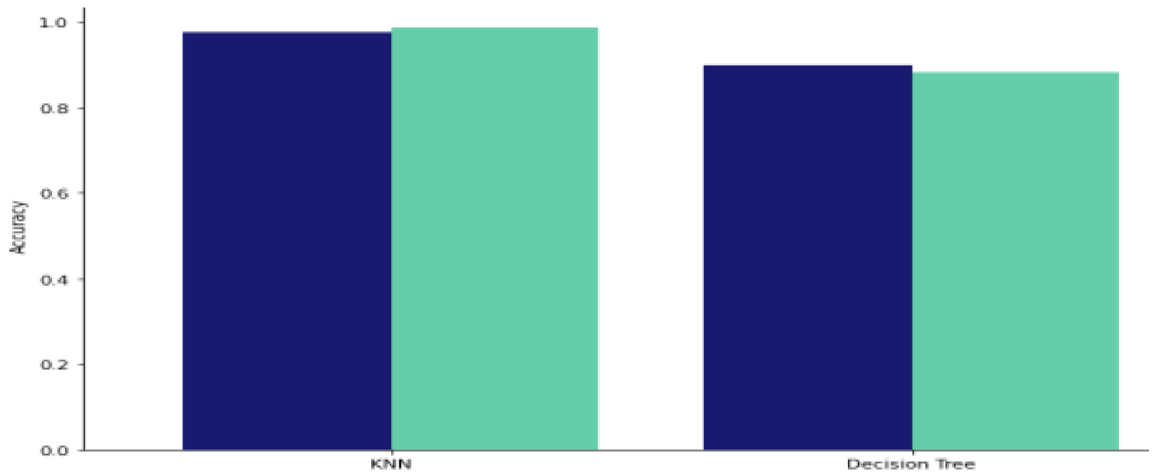

Fig 1: Accuracy graph

KNN VS Decision Tree:

On training the data set with KNN and Decision tree we had found the KNN had more and accuracy compared to Decision tree and end results conclude that KNN have 97.5% and Decision tree just have 90% Accuracy The provided graph compares the accuracy of K-Nearest Neighbors (KNN) and Decision Tree models. The dark blue bar represents the accuracy of KNN, and the light green bar represents the accuracy of the Decision Tree model. From the graph, it's evident that the KNN model has a higher accuracy than the Decision Tree model. This is shown by the slightly taller blue bar for KNN compared to the green bar for the Decision Tree. Therefore, based on this visual representation, the KNN model demonstrates superior performance and is the better choice for achieving higher prediction accuracy in this context.

V. CONCLUSION

The evolution of Deep Learning marks a significant advancement in Artificial Intelligence algorithms, fostering self-reliance and intelligence. Motivated by this progress, a novel crop yield prediction system is proposed, demonstrating its effectiveness and versatility through precision and efficiency tests. The proposed K-Nearest Neighbors (KNN) algorithm facilitates self-exploration and experience replay within a yield prediction environment, enabling the agent to learn crop yield prediction autonomously. Results from dataset predictions showcase the agent's ability to administer the process accurately, indicating the method's capability to define crop yield characteristics precisely. The integration of KNN-based feature processing is pivotal in achieving favorable outcomes. Unlike supervised learning-based methods, KNN autonomously mines the non-linear relationship between crop yield and environmental parameters, reducing expert dependency and prior knowledge requirements. However, it's crucial to acknowledge potential challenges such as data dimensionality or scalability, particularly with larger datasets. Incorporating a wide range of Machine Learning (ML) predictive algorithms for data prediction is beneficial for decision-making, but interpreting statistical uncertainty is essential. Therefore, designing a framework that predicts both targets and their uncertainties is necessary, with potential strategies including probabilistic predictive modeling and ensemble learning approaches. Future extensions of the model could explore ensemble methods like Random Forest or Gradient Boosting for enhanced performance. Additionally, incorporating more parameters related to pest infestations and crop damage would contribute to constructing a more robust model. Improving the computational efficiency of the training process remains an intriguing avenue for further research and development.

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