

Explainable Recommendation System for Smart Agriculture Farming with Improved Food Productivity

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Abstract: Use of advanced methods like Internet of Things (IoT), Artificial Intelligence (AI), Machine Learning, Drones, Big Data analytics to improve sustainability, productivity, and efficiency of agricultural practices is known as "Smart Agriculture". "By integrating sensors and automated systems into farming environments, smart agriculture enables real-time monitoring of soil conditions, weather patterns, crop health, and livestock behavior. This data-driven approach allows farmers to make informed decisions regarding irrigation, fertilization, pest control, harvesting, reducing waste and optimizing resource use. The Explainable Recommendation System for Smart Agriculture Farming, which is part of the suggested paradigm, uses a new Permutation Flamingo Optimized Recommendation System (PFO-RS) to increase food productivity. For farmers and other agricultural stakeholders, the system incorporates explainable Artificial Intelligence (XAI) concepts to guarantee openness and confidence in decision-making procedures. Fundamentally, the PFO-RS makes use of the Flamingo Optimization Algorithm, a metaheuristic method inspired by nature, to intelligently carry out feature extraction and permutation-based selection from intricate agricultural datasets, such as historical yield data, crop type, soil quality, and weather conditions. Only the most significant and pertinent aspects are taken into account when making recommendations thanks to this permutation technique. After the best feature subset has been identified, it is fed into a deep learning model that creates accurate and flexible agricultural recommendations based on particular farm conditions. These recommendations include the best crop choices, irrigation times, and fertilizer applications. In order to improve accuracy, the deep learning model continuously updates its suggestions based on real-time inputs and previous patterns.

Keywords: Smart agriculture, IoT, AI, explainable artificial intelligence (XAI), decision-making

I. Introduction

Humanity's existence and fortune have always been largely dependent on agriculture. Its development has been closely tied to changes in the industrial paradigm. Each industrial revolution has left its mark on agriculture—from the very first steam and mechanization of Industry 1.0 to the present-day phenomenon of the Industry 4.0, where automation meets data-driven decision making in agriculture [1]. Compared to all historical revolutions, which have had a strong influence on the

advancement of agriculture, the precision farming revolution in Agriculture 4.0 has brought more advanced electronic technology and significant improvements in IT for such an integrated approach as opposed to the Agriculture 3.0 phase. However, it ought to be clear that the particular challenges facing agriculture prevent the sector from speedy adoption of these emerging technologies, such as poor IT infrastructure and lack of experience. Important among space technologies is improving soil quality and decreasing water wastage through efficient irrigation systems. It facilitates sharing agricultural knowledge among farmers themselves. Sustainable implementation of smart agriculture [2] systems would necessitate science and innovations, including space technology, to increase the quantity and quality of agricultural outputs. It has to do with a combination of collecting, analyzing, and utilizing geospatial data from different sources such as satellites, surveillance and terrestrial, aquatic, and aerial sensors. Precision farming is used in modern intelligent agriculture because it ensures that the inputs will be in the right amounts and at the right times to maximize production and reduce environmental impact. AI-embedded predictive analytics makes it easier to predict the market trends and diseases in crops, allowing better risk management and planning. The primary role of Explainable Artificial Intelligence (XAI) in smart agriculture is to improve transparency, trust, and actionable knowledge in AI-based farming methods. AI models are often described as "black boxes," thereby making it difficult for farmers as well as agronomists alike to understand the rationale behind the results produced by such systems, although these systems may deliver accurate predictions in tasks such as crop disease diagnosis, yield prediction, or soil analysis [3]. In such scenarios, XAI offers a short account of its reasoning behind calling a certain decision, enabling more interested parties to go through the rationale behind the recommendations and even confirm it. For example, a smart irrigation system may explain why a certain amount of water is prescribed for a given field region based on the crop type, temperature, and soil moisture. Interpretability is for increasing confidence in system adoption by users, and it also has a role in enabling domain experts to uncover possible biases or mistakes that the models may contain. This smart farming has revolutionized agricultural operations through the use of ML and AI for optimizing crop yield and management. Combining these has given way to development of advanced CR systems that intelligently recommend crop cultivation based on various factors such as soil properties, prevailing weather conditions, previous yield records [4]. These systems target cost and environmental efficiencies while improving productivity and profitability in agriculture. The fact that the ML models are opaque is a huge barrier to the practical adoption of AI-based CR systems in agriculture despite the fact that they obviously have some benefits. Most of such models work as "black boxes," producing predictions without justification. The lack of openness may render farmers, who generally make judgement based on actual information and experience, unskeptical and intolerant. Lack of comprehension of the reasoning behind AI suggestions erodes confidence and prevents smart agricultural solutions across the board [5]. In addition to trust issues, model transparency also entails legal requirements such as that in General Data Protection Regulation (GDPR), which assures the right to explanation. "The present rule underlines the fact that effective and reasonable explanations must be established with regard to the automated decision impacting a particular person. This also applies to having smart farm CR systems elucidating the reasoning by which such suggestions have been offered. Explainable AI (XAI) is probably the solution to these issues[6]. The purpose of XAI is to make it possible for humans to understand the modes of decision-making in the AI systems," says a source on AI research. The CR system thus may reveal factors that determined the recommendations that would be made to the

particular farm. To do this, use methods such as SHapley Additive ExPlanations (SHAP), Differentiable Counterfactual Explanations (dice_ml), and Local Interpretable Model-agnostic Explanations (LIME). Although these interpretations can be global in nature, indicating the model's overall behavioral tendencies, or local, supporting specific predictions. The aim of theoretical foundations in XAI is to bridge the gap to this increasing use in many fields with the call for systems—AI systems—that should be trustworthy, equitable, and accountable. In smart farming, XAI acts as an interface between farmers and AI systems, providing valuable and actionable information for farmers to make decisions. This conversation aims at creating a collaborative milieu between human expertise and AI capabilities by suggesting answers and letting farmers articulate the right questions [7, 8].

1.1 Contribution for this research:

In order to methodically create and execute the Explainable Recommendation System for Smart Agriculture utilizing the Permutation Flamingo Optimized Recommendation System (PFO-RS), the proposed work is divided into multiple clearly defined parts. IoT sensors, satellite imaging, agricultural databases are utilized to collect a variety of agricultural data in the first phase, including soil characteristics, crop varieties, insect patterns, climate, and past yields. To clean data, deal with missing values, bring it to a consistent scale appropriate for analysis, the second phase involves data preparation and normalization. The Flamingo Optimization Algorithm, which cleverly finds and permutes the most pertinent factors influencing food productivity, is used in the third phase to concentrate on feature extraction and selection. In order to produce accurate agricultural suggestions, the fourth process involves building and training a deep learning-based recommendation system using the optimized feature set. Explainability modules, which are incorporated into the fifth phase, allow the system to transparently explain the rationale behind particular recommendations, hence increasing user adoption and trust. The usefulness of the system in actual smart farming settings is evaluated in the sixth step using a performance evaluation and validation procedure that uses measures including accuracy, precision, recall, and productivity improvement rate.

1. Literature survey:

Current agricultural research initiatives regarding crop forecasting include those by Work [9], who developed a model for crop prediction using Gaussian Naive Bayes, Decision Tree, Logistic Regression, Random Forest, XGBoost as baselines. Authors conducted training of those models on data gathered from various sectors of Indian agriculture. Such researchers ended up developing an Android app that can use both offline and online platforms for the forecasting based on the created models. By similar standards,

author [10] created AgroConsultant, an intelligent recommendations system that guides Indian farmers in choosing a crop to grow depending on various geo and environmental parameters. It utilized a soil dataset collected from various sources to assert the proposed approach [11]. Using the ensemble model of the system, the output was rule-based. In the same vein, author [12] tried adopting ensemble techniques to construct a highly efficient and logically accurate crop recommendation system as well. In Random Forest, CHAID, K-Nearest Neighbor, Naive Bayes learners, they used the technique of majority voting. The dataset for this research study was crop data sourced from the internet and soil testing laboratory data. Hence, such a rule was demonstrated by the application of the most relevant model. A crop recommendation module was developed by Work [13] based on the majority voting scheme by combining the outputs of SVM, RF, NB, KNN. It also developed a TILLAGE web-based tool based on a very catchy module that provides recommendations on pesticides and fertilizers. The modular approach is suggested to elevate agricultural productivity by improving crop selection, fertilization and soil use. Study [14] showed how agriculture has grown in high dimensions of rich countries based on crop and soil factors. for supporting small and marginal farmers in the state of Kerala, India. Crop calendars and soil-crop databases were prepared from observations in the various cultivated fields. This was done by cheapening the cost of agriculture using various electrical tools. In the study, data on soil-weather parameters, i.e., temperature, humidity, NPK (nitrogen, phosphorus, and potassium) values, and Potential of Hydrogen (pH value), were gathered over time through in-situ observations. The authors found, after collecting and analyzing data through a wireless sensor network communicating with a remote server, that the MAC and routing algorithm method showed promising results. A networking and sensor model for environmental condition data gathering on fields of white cabbage crops was proposed in work [16]. Diesel non-reduction and monitoring of environmental requirements on the growing farm. A very short essay on precision agriculture reduce labor costs and solve food problems-author [17]. The Active Precision Farming Process was authored by the authors who considered the different steps of Active Precision Farming to address daily problems of climate change and pollution caused by work [18] in which sensor was proposed to collect data on the leaf temperature and its water requirement. By knowing this, it sets and uses the crop requirements and period-specific adaptability to allow improved farming. The use of EM4325 ultra-high-frequency (UHF) chips and sensors based on Radio-frequency identification (RFID) were parts of the whole theme tackled by the writers. The author [19] further can supply alternative strategies that could be proposed for the improvement of crop productivity. Variety of Technologies Used for Agricultural Production: These are the following: Connectionless Mode Service (CLS), Packet Switching (PS), and Physical Layer Signaling (PLS). PLS precision sowing has been said to improve crop yield more effectively. Work [20] discusses the way Internet of Things (IoT) enables inter-connection between devices, such as

smartphones, tablets, PCs, through machine-to-machine (M2M) communication. They discuss the applicability of IoT towards precision agriculture through best utilization of resources such as water, light, pesticides, thereby improving production efficiency and decreasing waste. Performance of our proposed method along with its superiority over other methods in various studies has been discussed in Table 1.

Table 1. A comparison between our suggested methods and performance analysis found in literature review.

Author	Proposed Model/Framework	Dataset	Algorithms or Techniques Used	Performance Analysis	Discussions (Pros and Cons)
Doshi et al. (2018)	An architecture for agro consultants that forecasts crop suitability.	India's climate and agriculture were the subjects of the dataset.	MLC, DT, K-NN, RF, NN.	NN with an accuracy of 91%.	An intelligent decision-making system that recommends crops according to soil characteristics and location. season, water, and temperature. There are two stages to the analysis of rainfall and soil properties.
Ranaweera et al. (2023)	a broad framework for predicting crop prices by analysing	The Sri Lanka vegetable dataset from 2018 to 2021 is used.	The evaluation metrics MAE and RMS are	The prediction accuracy of RF is 85%.	Based on factors including temperature, rainfall, fuel prices, and

	historical data with machine learning tools.		applied to LR, SMO, multilayer, RF, and M5P.		agricultural production rates, machine learning algorithms are used to estimate crop prices.
Bondre, D. A. et al. (2019)	System architecture for crop production forecasting, fertiliser advice, and soil categorisation.	For five years, data on wheat, chill, onion, rice, soybean, sunflower, tobacco, and other crops was gathered from various sources.	RF and SVM.	SVM with 99.47% accuracy.	An architecture that uses machine learning algorithms to classify soil, predict crops, and provide fertiliser is suggested and then further validated for optimum match. The most accurate method for predicting agricultural yield is the SVM.
Thilakarathne, N. N. et al. (2022)	An illustration of the crop recommendation platform, which uses AI models to make predictions and is created as a web application	2200 records with 8 features—such as climate, fertiliser demand, rainfall, etc.—were gathered	SVM 0.1.0, XG Boost 2.1.0, RF 1.1.0, NN 0.1.1, and DT 1.1.64 algorithms	RF with 97.18% accuracy.	To help farmers with crop recommendations, a cloud-based machine learning-powered crop recommendation

	that is hosted in the cloud.	from Kaggle to create the crop recommendation dataset.			platform was suggested. Based on various measuring factors.
Priyadharshini et al. (2021)	A crop recommendation system based on historical data analysis was proposed.	Dataset for 16 different crop kinds was gathered from government websites and Kaggle. The many datasets that were gathered are yield datasets, rainfall, soil nutrients, crop model pricing, and cultivation costs.	A variety of ML methods were utilized.	According to method, NN has best accuracy, at 89.88%.	Crop profit, recommendation, and sustainability have been analysed and identified using a historical dataset from Kaggle.
Rajak et al. (2017)	Make a voting classifier model for suggested crops.	Maharashtra's Politest Labs provided the soil dataset, while Marat Wada University provided the agricultural data.	Voting classifiers, SVM, and ANN 0.1.0 were among the techniques used.	With an average accuracy of 97%, ensemble SVM, ANN, and RF perform better when combined	The ensemble voting classifier analysis yields more accurate crop recommendations.

				with majority voting.	
Ishak, M. et al.	Techniques for forecasting, tracking, and analysing crop yields.	The dataset was gathered between 2013 and 2019 in 64 districts throughout Bangladesh.	Voting Ensemble Regressor, RF, SVM were used.	R2 and RMSE are used to measure performance, voting regression has greatest R^2 value of 82.8%.	It implemented crop recommendations for six distinct crops based on following specifications: district and crop price.

3. Proposed Method

The proposed model comprises an Explainable Recommendation System for Smart Agriculture Farming aimed at improving food productivity through a novel Permutation Flamingo Optimized Recommendation System (PFO-RS). The system integrates XAI principles to ensure transparency as well as trust in decision-making processes for farmers and agricultural stakeholders. At its core, the PFO-RS utilizes the Flamingo Optimization Algorithm, a nature-inspired metaheuristic technique, to intelligently perform feature extraction and permutation-based selection from complex agricultural datasets, including soil quality, crop type, weather conditions, historical yield data. This permutation mechanism ensures that only the most relevant and high-impact features are considered for generating recommendations. Once the optimal feature subset is derived, it is fed into a deep learning model that constructs precise and adaptive farming recommendations—such as optimal crop selection, irrigation schedules, and fertilizer application—tailored to specific farm environments. The deep learning model learns from historical patterns and real-time inputs, continuously updating its recommendations for enhanced accuracy. The explainability component of the system provides interpretable justifications for every recommendation, empowering farmers to make informed decisions with confidence.

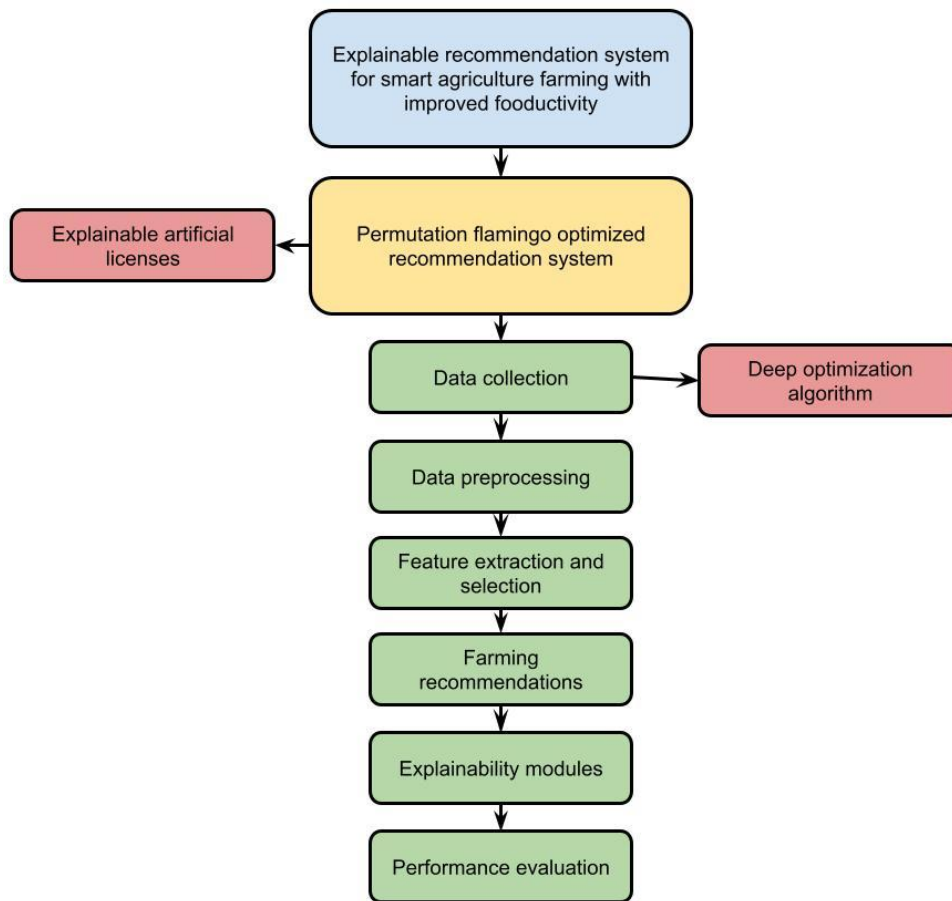


Figure 1: Flow chart of the Proposed PFO-RS

The proposed work is structured into several well-defined phases to systematically develop and implement the Explainable Recommendation System for Smart Agriculture using the Permutation Flamingo Optimized Recommendation System (PFO-RS) as shown in figure 1. The first phase involves data collection, where diverse agricultural data such as soil properties, climate conditions, crop types, pest patterns, historical yields are gathered from IoT sensors, satellite imagery, and agricultural databases. In the second phase, data preprocessing and normalization are performed to clean the data, handle missing values, and bring it to a uniform scale suitable for analysis. The third phase focuses on feature extraction and selection using the Flamingo Optimization Algorithm, which intelligently identifies and permutes the most relevant features affecting food productivity. This is followed by the fourth phase, where the deep learning-based recommendation system is constructed and trained on the optimized feature set to generate precise farming recommendations. The fifth phase incorporates explainability modules, enabling the system to provide transparent insights into why specific recommendations are made, enhancing trust and adoption among users. Finally, in the sixth phase, a performance evaluation and validation process is

conducted utilizing metrics such as accuracy, precision, recall, productivity improvement rate to assess effectiveness of system in real-world smart farming scenarios.

3.1.1 Phase-1: Dataset collection:

To gauge the effectiveness of both new and existing models, three core datasets were employed: weather, soil, and crop data. This data encompassed key elements influencing crop forecasts, such as soil characteristics, weather conditions, agricultural practices, and was collected from 34 districts across South India over period from 2001 to 2015. Data was meticulously organized into 3 distinct datasets, every reflecting relevant factors.

STATISTICAL CHARACTERISTICS OF DATASET: a comprehensive summary of soil characteristics across five districts: Anantapur, Chittoor, Guntur, Kadapa, and Nellore. In terms of nitrogen levels, Anantapur and Kadapa exhibit low concentrations, Chittoor shows medium levels, while Guntur and Nellore also present low levels. Phosphorus levels are consistently low throughout all districts. For potassium content, Anantapur has medium levels, whereas Chittoor, Guntur, Kadapa, and Nellore report low levels. The soil types vary among the districts: Anantapur and Chittoor have red soil, Guntur features black soil, Kadapa has a combination of red and black soil, and Nellore is characterized by alluvial soil. Soil depth also differs, with Anantapur and Kadapa having depths ranging from 100 to 300 cm, Chittoor having a very shallow depth of 0 to 25 cm, and both Guntur and Nellore showing a depth of 300 cm. Lastly, the pH levels vary: Anantapur soil is neutral, Chittoor's is slightly acidic, Guntur's and Kadapa's soils are strongly alkaline, and Nellore's soil is slightly alkaline.

Table 1 provides a detailed overview of weather characteristics recorded in Adilabad over five years: 2001, 2002, 2003, 2004, and 2005.

Pressure: The atmospheric pressure data shows a slight increasing trend over the years, ranging from 95.623 in 2001 to 97.998 in 2005. ◦ Temperature: The average temperature exhibits a gradual increase from 27.152°C in 2001 to 28.999°C in 2005. ◦ Humidity: Relative humidity significances are also on the rise, starting from 12.345% in 2001 and reaching 12.985% by 2005. ◦ Wind speed: Wind speed measurements show a gradual increase over the years, from 3.158 m/s in 2001 to 4.125 m/s in 2005. ◦ Maximum temperature: The highest recorded temperatures each year slightly increase, from 47.125°C in 2001 to 47.985°C in 2005. ◦ Minimum temperature: The lowest temperatures recorded have a minor fluctuation, ranging from 8.125°C in 2001 to 8.645°C in 2005.

Table 1. Statistical characteristics of weather dataset (Adilabad District).

Year	2001	2002	2003	2004	2005
Pressure	95.623	97.458	97.125	97.859	97.998
Temperature	27.152	28.365	28.56 .5	28.758	28.999
Humidity	12.345	12.189	12.457	12.680	12.985
Wind Speed	3.158	1.247	3.654	3.989	4.125
Maximum temperature	47,125	47.352	47.555	47.689	47.985
Minimum temperature	8.125	× 328	8.457	8.325	8.845
Cloud amount	56.145	48.528	47.135	55.9%	53.689
Precipitation	3.225	3.105	3.454	3.565	3.689
UVA Irradiance	14.588	14.254	14.168	14.609	14.578
UVB Irradiance	0.458	0.425	0.498	0.512	0.524
Downward Irradiance	6.145	6.245	6.347	6.458	6.788
PAR Total	100.125	98.562	99.347	99.858	98.858

Table 2. Statistical characteristics of agricultural dataset (Anantapur District).

Crop type	Year	Area (1000 ha)	Yield (Kg per ha)	Irrigated area (1000 ha)
Rice	2001	71	2880.561	70.944
	2002	40	2150	39.925
	2003	28.341	2482.361	28.325
	2004	33.588	3176.599	33.504
	2005	48.155	2607.688	48.066

Cloud amount: The cloud cover percentage varies year-to-year, with a high of 56.145% in 2001 and a low of 47.135% in 2003, with some fluctuations in amid. ◦ Precipitation: Annual precipitation amounts show a gradual increase, starting at 3.225 mm in 2001 and reaching 3.689 mm by 2005. ◦ UVA irradiance: UVA irradiance levels vary slightly from 14.588 W/m² in 2001 to 14.578 W/m² in 2005, indicating a relatively stable level of ultraviolet A radiation. ◦ UVB irradiance: UVB irradiance levels increase marginally from 0.458 W/m² in 2001 to 0.524 W/m² in 2005. ◦ Downward irradiance: The downward irradiance, which measures the amount of solar radiation reaching the Earth's surface, shows a steady rise from 6.145 W/m² in 2001 to 6.788 W/m² in 2005. ◦ PAR total: Photo synthetically active radiation (PAR) exhibits some fluctuation, with significances ranging from 100.125 W/m² in 2001 to 98.858 W/m² in 2005.

Table 2 provides a detailed account of rice cultivation in Anantapur from 2001 to 2005. It includes key metrics such as the cultivated area, yield, and irrigated area for each year. In 2001, the area under rice cultivation was 71,000 hectares with a yield of 2880.561 kg per hectare and an irrigated area of 70.944 hectares. Over the following years, the area dedicated to rice farming fluctuated, decreasing to 40,000 hectares in 2002 and further to 28.341 hectares in 2003. By 2004, the area increased to 33.588 hectares and further rose to 48.155 hectares in 2005. The yield also varied significantly, starting at 2880.561 kg/ha in 2001, dropping to 2150 kg/ha in 2002, and then increasing to a peak of 3176.599 kg/ha in 2004 before declining to 2607.688 kg/ha in 2005. The irrigated area followed a similar trend, initially at 70.944 hectares in 2001, reducing to 39.925 hectares in 2002, and further decreasing to 28.325 hectares in 2003. It slightly increased to 33.504 hectares in 2004 and then rose again to 48.066 hectares in 2005.

3.1.2 IoT based sensors in field area for crop prediction

Soil moisture sensors, soil pH level sensors, temperature sensors, humidity sensors are deployed to measure some of the other specifications in that area such as rain, pH value of the soil, and soil moisture level. These measurements are used to inform planting decisions on what crops should be planted. In order to analyze infected crops by utilizing mobile device's camera, pictures are taken and uploaded into the cloud to identify the ideal fertilizer recommended for it. The information stored in the cloud will thus be subjected to guidelines for data processing. Then, the dataset will be divided into training dataset and testing dataset. Data belonging to training dataset should be used for the crop recommendation training model to apply the deep learning algorithm. By providing pictures of afflicted croplands, it pulls information from databases for crop disease segmentation in event of crop diseases. Algorithms for image processing will then use the features that were extracted to forecast crop disease.

3.1.3 Phase-2: data Pre-processing:

Pre-processing data can enhance the quality of that data before feeding it into the model. It provides a coherent structure to the data model by addressing the deficiency of data, detecting redundancy in data, and disqualifying low quality data. This process has two phases. Firstly, it deletes the missing values (represented using a dot, '.') from the actual data. It preaches the raw data collected into machine-learnable datasets. This method does not require any labelling whilst performing data pre-processing for the numeric data in their values. This is done to allow data to be more trainable through normalization. Labels must be created during data pre-processing because the original dataset does not carry any. From yield and area of cultivation (tonnes and hectares), the labels of each crop are generated. The number 1 signifies those for whom the production area value was greater than zero. Class label 0 is set in all other

instances. At this stage, do some data management, formatting, and missing value handling. Work with missing values through imputation of feature means; see Algorithm 1. Environmental values show patterns as crop production is a continuous affair in a country. Thus, mean of the values before and after missing values in our dataset can hold the missing values.

Consider three different kinds of data: the amount of crop production in a certain area, the areas of cultivation, and environmental factors associated with crop production. These facts are gathered by us from various government agencies. Combine all of the data into a single dataset in order to prepare the learnable dataset. Junk, redundant, and unnecessary data negatively impact the ML models' performance.

Algorithm-1: data pre-processing

Input: Raw data (S)

Output: Pre-processed dataset after missing value handling

procedure Missing Value Handling(S)

for every attribute S^a do

$m^a = \text{mean}(S^a)$ [m^a is arithmetic mean of attribute S^a]

for every sample data S_d^a do

if S_d^a is missing then

$S_d^a := m^a$

end if

end

3.1.4 Phase-2: feature extraction and selection using Flamingo Optimization Algorithm

The above problems are solved using the flamingo optimization algorithm, which is a new swarm intelligence optimization method inspired by migration as well as feeding behavior of flamingos. Most flamingos are social migratory birds that eat algae, clams, tiny worms, and insect larvae. Another one is the way flamingos intertwine their long necks down and tilt them over for feeding. They have two important behavioral traits: foraging and migration. Most flamingo populations live in areas where they can forage abundantly. After a period of intense foraging, flamingo populations may migrate when food becomes insufficient in a particular area to sustain population. Foremost optimization concepts of FOA are provided as follows.

Flamingos find food sources in their current search area insufficiently abundant. Rather than locating more food within search region than in their known foraging areas, they prompt each flamingo to reset location. It turns upside down the FSA optimization path to find global optimal solution (GOS) inside a certain search region. Search agent will not be able to find the present GOS if it is in active search. In FOAS, flamingos are search agents that explore search space through exchange of information and move according to rules of stable position change that ultimately lead toward best answer. • The flamingo's activity, including its foraging and migrating habits, dictates the rules for changing postures. Additionally, the flamingos' foraging behavior is divided into two categories: foot movement and beak scanning. These traits impede their ability to forage.

(i) Scavenging behavior

Sociable behavior: The flamingo that finds the food will first alert the other flamingos, forcing them to adjust their positions to match the food's placement. Mathematically represent the availability of food in k th dimension as yd_k if the flamingo seeks the optimal solution, which is where there is an abundance of food.

(ii) Fitness function

The best flamingo is regarded as the fittest solution that offers the finest candidate solution after each flamingo's fitness function is assessed by eqn (1)

$$f(x) = 100(x_1^2 - x_2)^2 + (1 - x_1)^2 \quad (1)$$

(iii) Bill-scanning behavior - In order to find its food, a flamingo submerges its head in the water. When it finds food, it swallows it upside-down, filtering out extra water and waste. The flamingos' scanning radius varies depending on the circumstances, and they bend their heads and search more intently when there is an abundance of food. In the k th dimension, designate y_{lk} as the location of the l th flamingo. Even if there is a chance of small errors happening, random errors can happen during information exchange and are overcome by using a conventional normal distribution. The flamingos' greatest travel distance can be mathematically stated as eqn (2)

$$A_1 = M_1 \times y_{d_k} + \lambda_1 + y_{lk} \quad (2)$$

The fluctuation in the flamingos' scanning range is represented by M_1 , which is initially assumed to be a random number with a uniform distribution and to be carried out at its greatest distance by eqn (3)

$$A_2 = M_2 \times |M_1 \times yd_k + \lambda_1 + y_{lk}| \quad (3)$$

λ_1 and λ_2 are random values in the interval $[-1,1]$, while M_2 is a random value that has a typical uniform distribution.

(iv) Claw locomotive behavior The flamingos' claws travel in the direction of the area with plenty of food. The search region is expanded because the flamingos cover $\lambda_1 \times yd_k$, which is the distance from the spot where there is a lot of food (ydk). The flow of the food-finding processes in the n th iteration is provided by eqn (4)

$$s_{lk}^n = \lambda_1 \times ys_k^n + M_2 \times |M_1 \times yd_k + \lambda_1 + y_{lk}| \quad (4)$$

The flamingo's location is updated with different locations and can be stated mathematically as eqn (5)

$$y_{lk}^{n+1} = \frac{(y_{lk}^n + \lambda_1 \times ys_k^n + M_2 \times |M_1 \times yd_k + \lambda_1 + y_{lk}|)}{R} \quad (5)$$

(v) Emigrating behavior The fitness value of the flamingos is determined by their ability to emigrate, and the emigrating flamingo is regarded as the fittest. When there is less food available, the flamingos move to a different location to find food where there is more. The following is a mathematical representation of the flamingo's emigration behavior by eqn (6)

$$y_{lk}^{n+1} = y_{lk}^n + \sigma(ys_k^n - y_{lk}^n) \quad (6)$$

(vi) Termination The procedure is stopped after the ideal solution has been found and the maximum number of iterations has been reached.

Algorithm-2: Flamingo Optimization Algorithm

Start

Input: ydk

Output: y_n^{n+1}

While ($n < n_{\max}$) # n_{\max} is maximal iterations

Scavenging behavior

If

Start: ydk

For Bill scanning behavior do

Maximum distance

$$A_1 = M_1 \times yd_k + \lambda_1 + y_g$$

Varying scanning range

$$A_2 = M_2 \times |M_1 \times yd_k + \lambda_1 + y_{kk}|$$

Claw locomotive behaviour

$$s_{lk}^n = \lambda_1 \times ys_k^n + M_2 \times |M_1 \times yd_k + \lambda_1 + y_{kk}|$$

Position update

$$y_{ik}^{n+1} = \frac{(y'_k + \lambda_1 \times yy'_k + M_2 \times |M_1 \times yd_k + \lambda_1 + y_{uk}|)}{R}$$

Emigrating behaviour

$$y_{ik}^{n+1} = y_{ik}^n + \sigma(ys_k^n - y_{ik}^n)$$

Check the stopping condition

End

3.1.5 Phase-4: deep learning-based recommendation system

Therefore, using specified climate and crop parameters, crop advice is given to the farmers. This sequential dependence is managed by RNNs, which are an enhancement of neural networks. Hidden state of RNN stores history in that it takes output from previous step as input to current step. In a conventional neural network, each data point is treated as a separate entity altogether. The model being proposed in the present study is a feedback-integrated RNN based on long-short-term memory. Each node of LSTM is characterized by three distinct gates: input (I), output (O), forget (F). G presents the updated input at current time-stamp T . The real value of each of these gate banks on the current input X_T and the previous hidden state H_{T-1} is shown as follows (7).

$$I_T = F(W_I X_T + U_I H_{T-1} + B_F)$$

$$F_T = F(W_F X_T + U_F H_{T-1} + B_F)$$

$$G_T = \tanh(W_C X_T + U_C H_{T-1} + B_C) \quad (7)$$

The node's updated value is calculated as follows (8):

$$C_T = I_T \cdot G_T + F_T \cdot C_{T-1} \quad (8)$$

The node state, previous output, and current node input are used to determine the gate value by eqn (9)

$$O_T = F(W_O X_T + U_O \cdot H_{T-1} + V_O \cdot C_T + B_O)$$

$$H_T = O_T \cdot \tanh(C_T) \quad (9)$$

Three RNN models—one for the region's minimum temperature, one for its maximum temperature, and one for rainfall prediction—were trained in this study. The vector used to organize the data in the set is $\{X(1) \dots, X(K)3\}$. For both seasonal and 90-day previous forecasting, the dataset is transferred to a $N \times M$ matrix with 90 target values expressed as follows and one input feature per row by eqn (10)

$$\{X(T), X(T + 1), X(T + 2), \dots X(T + 90)\} \quad (10)$$

K represents size of time series data. The LSTM has the property of making a prediction for the weather, hence k-90 means that two dimensions N and M are 91. Model is divided into three layers: input, hidden, output. Hidden layer has four LSTM nodes. Min. The rainfall compared with temperature predictions has a similarity. The input layer receives a variety of data features from data. After this, processed data goes to middle layer by input layer. It contains many hidden layers within it. Every hidden layer has a unique weight, bias, and activation function. LSTM-RNN is used since weather conditions depend on the past.

Data Attributes

Agronomic researchers have known all this while, how various geographical and climatic conditions, such as soil type, altitude, rainfall, humidity, and temperature affect production, health, and growth of crops. The fitness of the crop in any geographical area will be determined by many factors in if individually or in combination.

Essential nutrients N (nitrogen), P (phosphorus), K (potassium), quality of the soil as reflected by pH are the parameters taken into consideration in the upcoming learning model. These facts are absolutely significant discretionary factors for crop recommendation and also markers across plenty of datasets. Hence, our model prediction gives the primary type of crop. Although it would be desirable to include all significant geographical and environmental factors for a comprehensive suggestion, the suggested study is mainly concerned with quality, nutrients, health of soil. The explanations are as follows:

- Consistency and Availability of Data: Our data comes from a variety of sources, most of which are concerned with crops, pH, N, P, and K. Variables like temperature and rainfall were present in some datasets, but in order to maintain consistency and avoid the introduction of data biases, uniform characteristics across all data points were required.
- Difficulty of Data Collection for Other elements: Compiling an extensive dataset that encompasses all climatic and geographic elements is an enormous undertaking.

Interrelation with pH: A few environmental factors can be substituted by the soil's pH, which shows how acidic or alkaline it is. For instance, frequent rainfall may have an impact on the soil's pH, which in turn may reflect humidity and temperature. By including pH, the model indirectly takes into consideration some of the effects of outside influences on soil.

Model Training

At same time, the study takes into consideration a validation set with 10 % contribution from the training dataset to indicate overfitting or underfitting during training. The training data comprises 7308 data samples, four predictors (N, P, K, and pH), single response variable, namely major crop. Since interaction between crop varieties and soil parameters is complex and nonlinear, study employed a NN, which could be described as an advanced machine learning model for analyzing difficult patterns and dependencies in data. Input selections for model should be stored in the input layer for best performance. Topologies with different numbers of hidden layers and nodes within every layer were explored for maximization of productivity. Based on empirical investigation and its results study found that two hidden layers with 64 and 32 neurons were taken into account. The nodes in the output layer represent the number of distinct crop types in dataset. It uses sparse categorical cross-entropy loss function. Fit() method accepts training data as well as informs model training. Out of the training data, a training subset and a validation subset are drawn. Validation takes place while training on 20% of the training data. Two hundred epochs train the model, with the input data divided into batches. Model uses gradients from a batch of size 64 to update its weights and biases in every iteration. Model uses Adam optimizer for updating and backpropagation for the algorithm applied in updating the weights and bias. In order to train the neural network efficiently for crop prediction with those factors, latent features and intricate patterns found in data points from training dataset are in charge. Algorithm 3 talks about the neural network's training procedure.

Algorithm-3: Deep learning model based crop recommendation

Input: x_{train} Training data (N, P, K, pH) y_{train} labels (crop),

Number of predictors η , Number of unique crop classes κ ,

Learning rate α , Number of epochs e , Batch size s , Adam

hyperparameters $\beta_1, \beta_2, \varepsilon$

Output: Trained NN method

Procedure:

1. Start:

Describe input layer with η

2. First hidden layer 64 with weights $W_1 \in R^{64 \times \eta}$ and biases $b_1 \in R^{64}$

4. Training: For epoch = 1 to e :

5. Shuffle training data.

6. Divide x_{train} and y_{train} into batches of size s

For every batch:

Evaluate: $Z_1 = W_1X + b_1$ and $A_1 = \text{ReLU}(Z_1)$

Compute: $Z_2 = W_1X + b_1$ and $A_2 = \text{ReLU}(Z_2)$

Compute: $Z_o = W_oA_2 + b_o$ and $A_o = \text{softmax}(Z_o)$

Evaluate Loss L

Evaluate gradient of loss w.r.t. final output $\frac{\partial L}{\partial A_o}$

Evaluate: $\frac{\partial L}{\partial z_o} = A_o - y_{\text{train}}$

$$\frac{\partial L}{\partial W_o} = \frac{\partial L}{\partial z_o} A_2^T$$
$$\frac{\partial L}{\partial b_o} = \frac{\partial L}{\partial z_o}$$

Utilizing chain rule and considering ReLU derivatives:

$$\frac{\partial L}{\partial A_2} = W_2^T \frac{\partial L}{\partial z_o}$$
$$\frac{\partial L}{\partial z_2} = \frac{\partial L}{\partial A_2} g'(z_2) // \text{ where } g' \text{ is ReLU derivative}$$

End

Explainable AI

Crop categorization systems are validated through use of XAI. It enables us to pinpoint the crucial elements in crop data that affect choices. By lessening the impact of noisy features, it verifies the accuracy of predictions. As a result, the model forecast will be impartial and equitable across various demographic groupings. All things considered, XAI validates the classification techniques by revealing features, fostering transparency, and encouraging error analysis.

4. Results and discussion:

Experimental setup- The proposed models were developed using Python on a system equipped with Microsoft Windows 10, an Intel(R) Core(TM) i7-10700 CPU @ 2.90GHz, 16.0GB of RAM, and 512 GB of SSD storage. Based on performance, compared several FSO-RNN_LSTM models and chose the best one. For this research, used a personal PC for execution. Table 3 lists all of the computer's specifications.

Table 3 System Configuration

Component	Specification
GPU	2x Nvidia Quadro p4000(8GB)
Storage	4TB
RAM	128GB
Processor	16x Intel(R) Xeon(R) Bronze 3106
OS	Windows Server 2016(64 bit)

Table 4 shows the error ratings for the suggested and studied methods of estimating rice production based on R2 score and various metrics.

Model	MAE	MSE	RMSE	R^2
SVM	0.108	0.017	0.126	0.970
Decision tree	0.103	0.018	0.135	0.950
XGBoost	0.094	0.011	0.111	0.980
GB	0.092	0.017	0.155	0.970
CNN	0.125	0.036	0.171	0.960
FSO-RS-RNN_LSTM	0.092	0.008	0.089	0.980

It shows how our method outperforms all other ensemble ML as well as standard ML methods. Calculate model good fit for rice production prediction with MAE, MSE, RMSE and R2 in Table 4, which proves that FSO-RNN_LSTM models better than all those spectra. It harms the production cycle and damages the crop. Our proposed FSO-RNN_LSTM indicates during this time how adaptable it becomes because of the uncertainty in environmental data. Post floods, effects on productivity last through the subsequent growing seasons from poor soil fertility and poor soil carbon management. A weather point is a point in where a specific weather data is shown for a specific location and moment. Temperature, wind direction, wind speed, humidity, and sun hours are combined to give the weather point in this work. Forty percent of the samples were used to make the predictions; the remaining 60% were used to train the model. Maximum temperature, minimum temperature, and rainfall are the three parameters used for the right seasonal crop prediction. Corresponding results for predicting these parameters are given in Figure 2.

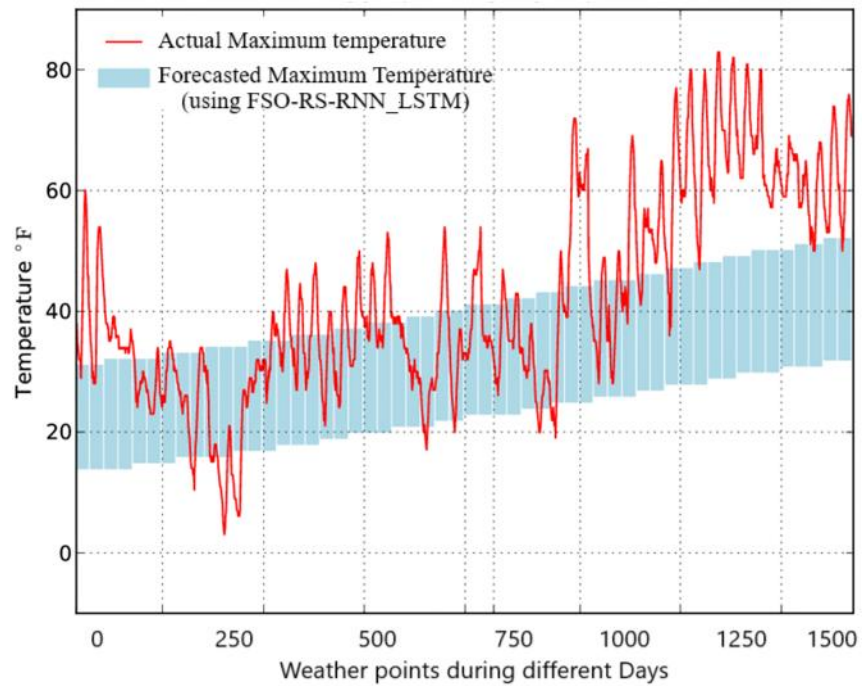


Figure-2 Max Temp prediction for 90 days.

In the training, the model has learned the underlying patterns very well with a training accuracy as high as 99%. But one should note that there cannot be 100% training accuracy always, which then leads to overfitting, where the model performs badly on unknown data and becomes too specific to the training set. This might indicate that there was variability within the validation set that the model could not capture, or it could also mean that the model overfitted to the training data. A 95% validation accuracy rate still represents a commendable level of accuracy and indicates that method generalizes well to new, unseen data. To summarize, very high accuracies during training and validation suggest an appropriate fit of method to data as well as good ability in producing accurate predictions.

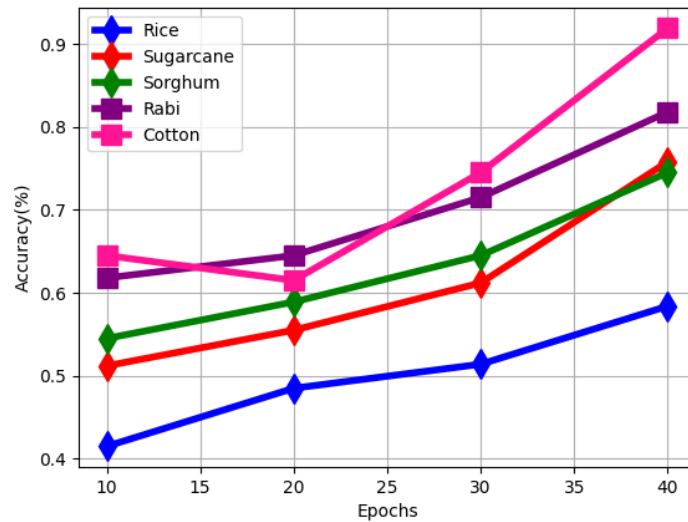


Figure 3. Training and validation curve for rice, sugarcane, sorghum, Rabi, and cotton

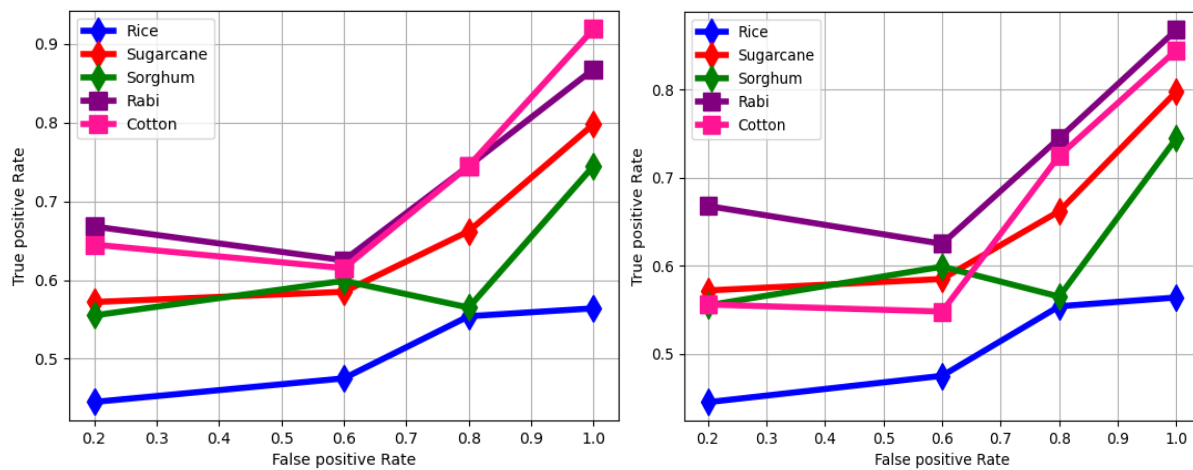


Figure 4. Analysis of ROC curve; (a) ROC plot; (b) Magnified view of overlapping ROC regions.

A popular metric for assessing how well categorization models work is ROC score. ROC score, which calculates a trade-off between True Positive Rate (sensitivity) and False Positive Rate (specificity), is based on outcome statistics displayed in Figure 4. A perfect classifier is represented by a ROC score of 1, whereas a method that is no better than random chance is represented by a score of 0.5.

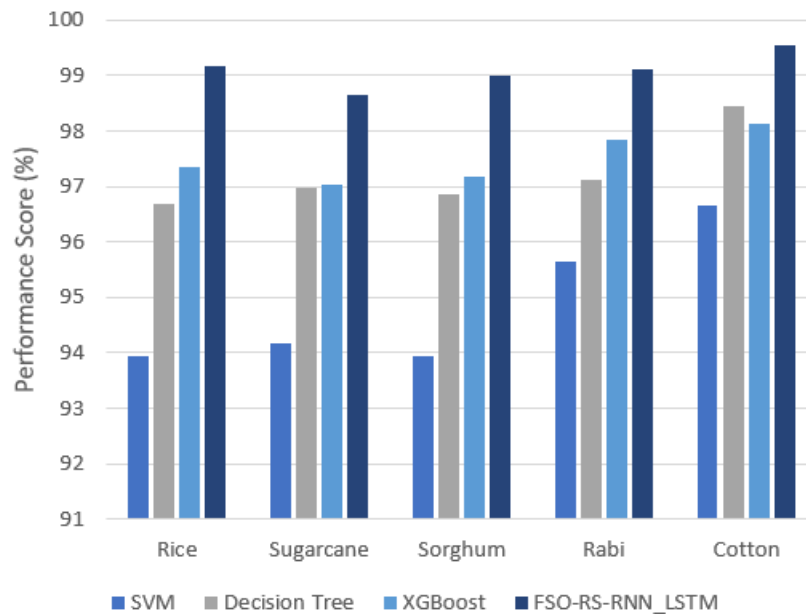


Figure 5. Comparative analysis with various predictive models.

Table 5. Accuracy comparison of recommendation models for precision farming.

Model	Accuracy (%)				
	Rice	Sugarcane	Sorghum	Rabi	Cotton
SVM	85.077	84.610	85.168	84.866	85.497
Decision Tree	85.646	85.179	85.737	85.435	86.066
XGBoost	86.214	85.747	86.305	86.003	86.635
GB	86.783	86.316	86.874	86.572	87.204
CNN	87.352	86.885	87.443	87.141	87.773
FSO-RS-RNN_LSTM	87.921	87.454	88.012	87.710	88.342

The proposed neural network model's applicability for specific tasks was assessed along with performance comparisons against other supervised classifiers in the study. The comparison was carried out to examine efficacy of proposed NN and 3 other methods-SVM, Decision Tree, XGBoost, GB, and CNN-which is shown in Figure 6. The performance evaluation was done using three important measures: weight precision, recall, and F1-Score-to look for any subtle differences in performance amongst different models. Outcome analysis indicated that proposed network methods surpassed all other methods, including SVM, Decision Tree, XGBoost, GB, CNN in this comparative analysis. Table 5 presents the accuracy of various recommendation models for precision farming across different crop types, including rice, sugarcane,

sorghum, Rabi, and cotton. proposed FSO-RNN_LSTM emerge as the top-performing model across all crops.

Crop recommendation- The final phase of any recommender system is typically execution. One sets an accepted threshold for this system above which the model will be able to predict the output for a region. The basis of recommendation is the actual yield of crops that will be identified against bio-physical data. In order to come up with a recommendation, the threshold, and predicted data for each crop season is compared. The most suitable crop for the given local season is what is recommended. The input parameters to the system are basically season and cropped list. Output to system is the recommended crop from the chosen crop list. Thus, a mobile application is envisioned as the next step of this project to help farmers in accessing this system more easily.

5. Conclusion:

The proposed paradigm, namely the Explainable Recommendation System for Smart Agriculture Farming, employs a unique Permutation Flamingo Optimized Recommendation System (PFO-RS) to enhance food production. The system incorporates explainable artificial intelligence concepts for farmers and other agricultural stakeholders to provide transparency and ensure trust in the decision-making processes. The system would eventually yield information that may aid farmers in crop selection decisions or fertilizer application through machine learning and data analytics. The neural network demonstrated its accuracy, balance and dexterity by beating many of the other prominent machine learning algorithms with detailed comparative studies. Besides promoting farming practices that are less expensive and more environmentally friendly, this system can also enhance crop productivity and quality. But the system has certain disadvantages. It needs more geographical, environmental factors beyond what this paper has covered, while data modelling, as well as feature extraction need improvement and expansion. Further data collection will be done in the future for this project, and deep learning techniques will be investigated that could help in more accurately determining suitable crops for a specific area. Price analyses of local and wholesale markets will also aid in the crop selection process for a particular location.

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