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ADVANCING SOIL NUTRIENT MANAGEMENT IN AGRICULTURE WITH INTEGRATING MACHINE LEARNING AND FUZZY LOGIC APPROACHES

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ABSTRACT

Agriculture faces multifaceted challenges that affect food security, sustainability, and economic growth. Soils serve as the foundation for food production. However, indiscriminate use of fertilizers has led to soil pollution and degradation, necessitating integrated nutrient management practices. Machine learning (ML) emerges as a transformative technology in agriculture, offering solutions across various domains. Fuzzy logic, with its ability to handle uncertainty and imprecision, complements machine learning in agricultural decision support systems. This paper explores the utilization of fuzzy logic for soil nutrient categorization and decision-making, along with the analysis of machine learning models for predicting soil fertility and crop yield and also examines the recommendation of suitable crops and fertilizers based on soil characteristics. These models leverage diverse algorithms such as K- Nearest Neighbours, Random Forest, Naive Bayes, Support Vector Machine, Decision Trees and ensemble classifiers to offer accurate predictions and recommendations. The integration of ML and fuzzy logic in agriculture represents a potential approach to tackling agricultural challenges, advancing sustainable soil management practices, and elevating crop productivity.

Problems in Agriculture

Global and local agriculture confronts a number of formidable obstacles that have an effect on food security, sustainability, and economic growth. Severe conditions including heat waves, floods, and droughts brought on by climate change reduce animal production and yields of crops. (Lobell et al., 2011). Water scarcity intensifies agricultural problems, particularly in arid and semi-arid regions. As demand for water increases, its resources decline due to pollution, overuse, and the effects of climate change (FAO, 2020). Soil degradation presents another concern, with erosion, salinization, acidification, and loss of fertility posing threats to agricultural productivity and sustainability (Lal, 2015). Pests and diseases continually affect crops and livestock, causing substantial losses in yield and economic returns, if left unmanaged (Savary et al., 2019). Moreover, the loss of biodiversity due to agricultural intensification, monoculture practices, and habitat destruction undermines ecosystem services critical for agricultural resilience and long-term sustainability (Tscharntke et al., 2012).

Rural poverty and food insecurity are a persistent challenge, particularly among small farmers in developing nations, who often lack access to markets, credit, technology, and resources necessary for sustainable agricultural practices (FAO, 2021). Food wastage and losses in the agricultural supply chain further aggravate global hunger, economic losses, and environmental degradation, highlighting inefficiencies in production, distribution, and consumption (FAO, 2019).

Soil Nutrient Management

Soil is one of the most important resource of agriculture. It is estimated that 95% of food is directly or indirectly produced on soils. Soils supply the essential nutrients, water, oxygen and root support that our food-producing plants need to grow and flourish (FAO, 2015), The quality and quantity of food produced solely depend on the soil health (Lal, 2015). An increase in food demand has led to the application of large quantities of fertilizers, resulting in pollution and degradation of the soil (Juhi Reshma et al., 2021). In the majority of areas, farmers are applying chemical fertilizers without soil testing which leads to a depletion of soil health. Deficient nutrients impact the growth of plants, plant physiological disorders and yield (Smith et al., 2022). Integrated nutrient management (INM) is the sustainable solution for healthy soil. INM plays a vital role in maintaining soil productivity, ensuring productive and sustainable agriculture, reducing inputs cost by using farm wastes, green manures, biofertilizers and growing leguminous crops (Balusamy et al., 2020).

Soil nutrient deficiency in Indian soil and its associated impact on crop yield has been widely acknowledged and reported (Pandey et al., (2016). Numerous policy initiatives have been taken both at the State and National level. The soil health card introduced by the Government of India in 2015, is the best example. Though awareness about this initiative among farmers is high, only a less followed the recommended rate of fertilizer application. Some of the emphasized problems are the delayed receipt of soil test reports after soil sample submission, shortage of soil experts and accessibility (Reddy, A. A. 2019).

The accuracy of soil testing outcomes and recommendations for fertilizers is reliant upon the quality of soil sampling (Ministry of Agriculture and Farmers' Welfare, 2020). A fertilizer recommendation system based on soil analysis should be designed to ensure widespread adoption by farmers (Reddy, A. A. 2019). A comprehensive approach to agricultural management can be achieved by integrating various computational techniques. Arogundade et al. (2021) present a system utilizing fuzzy logic for soil fertility analysis and decision-making, while Ahmed et al. (2021) propose a soil fertilization system that merges evolutionary algorithms with soil nutrient data and crop requirements. Mahagaonkar (2019) focuses on crop yield prediction and fertilizer recommendation using machine learning algorithms. Thus, a recommendation system for farmers on integrated soil nutrient management can be developed for specific crops based on the assessed soil nutrient status, thereby improving soil health and crop production (Mella and Venkata, 2022).

Machine Learning

Machine learning (ML) is a process by which computers acquire the ability to execute tasks similar to those carried out by humans. Typically, ML empowers systems to autonomously improve and acquire knowledge from experience, without explicit programming. It is one of the leading technology developments in the current era, often associated with the fourth industrial revolution (Sarker, 2021). ML is a subset of Artificial Intelligence (AI) dedicated to learning. It enhances performance prediction by analyzing multiple features, identifying patterns, correlations, and insights from datasets and past experiences. Numerous models are constructed with various features and parameters based on historical data. Testing evaluates performance using unused historical data (Klompenburg et al. 2020).

"Machine learning" was coined by Arthur Samuel in 1959, pioneering AI in computer gaming. It evolved from early chess programmes in the 1940s to the development of neural networks and deep learning. This was due to the significant contributions of pioneers like Nilsson, Duda, Hart, Hinton, Ng, Bengio, and LeCun, who laid the foundation of modern neural network technologies (Sharma et al., 2021). Three key phases of ML are data input, model construction, and generalization (Fig 1). 'Generalization' entails predicting outcomes for inputs not included in the algorithm's training data. However, ML algorithms demonstrate proficiency in addressing complex challenges where human expertise may be insufficient, for example, weather prediction, spam identification, plant disease diagnosis, pattern detection, etc. (Sharma et al., 2020).

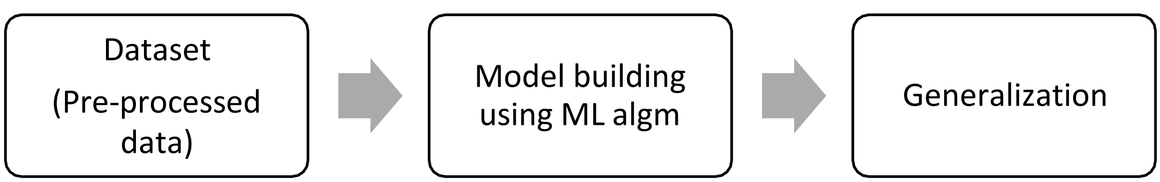

Fig 1: A Machine learning process

Classification of Machine learning techniques

Machine learning algorithms can be mainly classified as supervised, unsupervised and reinforcement learning paradigms. These serve tasks including classification, regression, clustering, and decision making, with diverse algorithms designed to suit each task's requirements and objectives. ML classification is important as it provides a framework that enables the selection of appropriate algorithms tailored to the specific nature of the data and the desired outcome (Sharma et al., 2020 and Liakos et al., 2018) as shown in Table 1.

i. Supervised learning, the algorithm is trained on a labelled dataset, where each example in the dataset is associated with a label or outcome. Here the goal is for the algorithm to learn a mapping from input data to output labels, enabling it to make predictions or decisions on new, unseen data.

ii. Unsupervised learning, the algorithm is given input data without any explicit labels or outcomes. The algorithm's task is to unfold the underlying structure or patterns in the data, for example, clustering similar data points together or reducing the dimensionality of the data.

iii. Reinforcement learning is a type of learning where an agent learns to interact with an environment to achieve a goal or maximize a cumulative reward. The agent takes actions in the environment, receives feedback in the form of rewards or penalties, and adjusts its behaviour over time to maximize its cumulative reward (Sharma et al., 2021).

Table 1: Categorization of ML algorithms

Category	Task	Algorithms
Supervised learning	Classification	- Decision Trees (DT)
		- Random Forests (RF)
		- k-Nearest Neighbours (KNN)
		- Support Vector Machines (SVM)
		- Naive Bayes (NB)
		-Neural Networks (e.g., Multi-layer Perceptron)
		- Gradient Boosting Machines (e.g., XGBoost)
	Regression	- Linear Regression
		- Polynomial Regression
		- Ridge Regression
		- Lasso Regression
		- Support Vector Regression
		- Decision Trees regression
		- Random Forests regression
Unsupervised	Clustering	- K-Means Clustering
learning		- Agglomerative Hierarchical Clustering
		- Density-Based Spatial Clustering of Applications with Noise (DBSCAN)
		- Gaussian Mixture Models (GMM)
		- Mean Shift Clustering
		- Fuzzy Clustering
Reinforcement learning	Decision making	- Q-Learning
		- R Learning
		- Q Learning
		- TD Learning

Application of Machine Learning in Agriculture

Machine learning finds applications in diverse areas, including stock price prediction, scientific research, marketing strategies, cyber security, e-commerce, mobile data processing, health analytics, user modelling, behavioural analytics, and clustering. These applications leverage historical data to make predictions and derive insights across various domains (Sharma et al. 2021) and (Sarker2021). Modern agriculture is also in the process of employing machine learning techniques. Machine learning can benefit farmers to minimize the losses in farming by providing recommendations and insights about the crops he is growing. Machine learning can be applied in agriculture to alleviate the problems in the three areas of pre-harvesting, harvesting and post-harvesting. The application of machine learning in agriculture allows more efficient and precise farming with less manpower for high-quality production (Meshram, 2021).

variables and membership functions of a fuzzy set (Prabakaran et al., 2018). Fuzzy logic systems operate on "if-then" rules defined using linguistic variables, capturing expert knowledge and heuristics to make decisions based on input data. The fuzzy inference process combines these

Machine learning is revolutionizing agriculture with its diverse applications. Crop yield prediction involves analyzing historical data, including weather patterns and soil conditions, to inform farmers about resource allocation and harvest planning. Disease and pest detection, facilitated by machine learning models trained on images of healthy and diseased crops, enables real-time identification of issues, reducing crop losses through timely intervention. Weed identification and management benefit from machine learning algorithms' ability to differentiate between crops and weeds, allowing for targeted herbicide application and minimizing environmental impact. Precision agriculture techniques, driven by machine learning technologies like Variable Rate Technology (VRT), optimize resource use such as water, fertilizers, and pesticides, resulting in improved crop yields. Additionally, machine learning recommendation systems process diverse data sources to offer personalized insights, from optimal planting times to irrigation schedules, empowering farmers with informed decision-making. Machine learning also extends its impact on livestock management, addressing animal welfare and enhancing livestock production practices (Liakos et al., 2018). The success of a machine learning solution depends on the type of data and the performance of learning algorithms, which include classification, regression, clustering, feature engineering, dimensionality reduction, association rule learning, and reinforcement learning techniques (Sarker, 2021).

Fuzzy Logic

Fuzzy logic is a mathematical system that addresses uncertainty and imprecision like human cognition. It was developed by LotfiZadeh in the 1960s as an extension of classical (crisp) logic, which deals with binary values (true or false). Conversely, fuzzy logic permits varying degrees of truth; something can be partially true or partially false.

In traditional set theory, an element either belongs to a set or not. Fuzzy sets, however, introduce the concept of partial membership. This means that instead of being strictly in or out of a set, elements can belong to a set to a certain degree, typically represented by a value between 0 and 1. Membership functions define how elements are assigned degrees of membership in fuzzy sets. These functions map the values of variables to their corresponding membership degrees. Membership functions can take various shapes, such as triangular, trapezoidal, or Gaussian, depending on the nature of the linguistic variable and the problem domain. Linguistic variables are variables whose values are expressed in natural language terms rather than numerical values. Each linguistic variable is associated with a set of linguistic terms (e.g., "Low", "Medium", "High" for "Temperature") and corresponding membership functions that specify the degree of membership for each term (Onashoga et al. 2018).

Fuzzification is the task of partitioning the input variable and assigning the linguistic label for each partition. It transforms discrete into a continuous form by linguistic rules and input data to produce a fuzzy output, which represents the truth values of possible output values. When a precise output is needed, defuzzification is applied as shown in Fig. 2 (Arogundade et al., 2021).

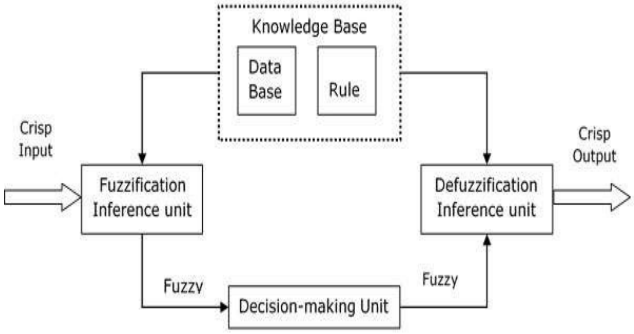

Fig 2: Fuzzy logic system

Fuzzy logic finds applications in fields such as control systems, artificial intelligence, and machine learning, particularly when handling uncertain or ambiguous data, enabling a more human-like approach to decision-making. It is utilized for making decisions when faced with uncertainty Alfin et al. (2017) and Jane and Ganesh (2019). The fuzzy logic model forms the core of the decision support system, which provides recommendations on fertilizer applications based on real-time or historical data input by the user. The system considers the uncertainty and imprecision inherent in agricultural data and provides flexible and adaptive recommendations. By using the fuzzy decision support system, farmers can improve crop productivity by applying the right amount of fertilizer at the right time and in the right place (Prabakaran et al., 2018).

Fuzzy Logic for Soil Nutrient Categorization and Decision-Making

Soil nutrient parameters are pH (reaction of soil), EC (electrical conductivity), OC (organic carbon), N (nitrogen), P (phosphorus), K (potassium), S (sulphur), Zn (zinc), B (Boron), Fe (iron), Mn (manganese), and Cu (copper). Soil nutrients have been classified as Physical (pH, EC, OC), Macronutrients (N, P, K), Secondary Nutrients (S), and Micronutrients (Fe, Zn, Cu, Mn, B). The nutrient status of the soil thus can be determined based on the physical, macronutrients, secondary nutrients and micronutrients of that soil (Paul et al., 2015).

Soil nutrient categorization classifies soils into qualitative categories based on the scale of optimum nutrient levels or indices. The category explains the nutrient status of the particular soil to the readings of nutrients of that soil as Low, Medium, or High. Traditional soil nutrient assessment methods often provide precise numerical values for nutrient concentrations. These values may not fully capture the inherent imprecision associated with soil properties and measurements. Fuzzy logic allows for the use of linguistic variables and fuzzy sets torepresent imprecise information more intuitively. The soil nutrient values can be converted to soil nutrient status using a fuzzy if-then rule method on a set range (Bang et al., 2019). Soil nutrient status is the backbone on which all input-based high agricultural production systems can be built (Lal, 2015).

Onashoga et al. (2018) presented a fuzzy logic-based decision support system design to aid in soil selection for vegetable cultivation. The system addresses the challenges of soil variability and complexity in agricultural decision-making processes. By utilizing fuzzy logic principles, the authors develop a framework that integrates various soil parameters and expert knowledge to recommend suitable soil types for specific vegetable crops. The system's usefulness is proven against conventional methods, showcasing its ability to provide accurate and intuitive recommendations for soil selection in vegetable farming. Fuzzy logic offers agricultural decision support systems for the suitable crop to be sowed based on soil management for improved yield. Fuzzy logic can be applied in predicting crop yield based on soil fertility parameters, thereby enhancing agricultural decision-making and optimizing crop production. Choudhary et al. (2022) introduce a fuzzy inference system designed to predict crop yield based on soil fertility parameters using MatLab. The soil dataset is obtained from Kaggle having attributes such as levels of N, P, K and pH, temperature, humidity, and rainfall. The study aims to address the challenges of uncertainty and variability in agricultural production by leveraging fuzzy logic principles. Through the integration of soil fertility data and fuzzy inference techniques, the authors develop a model capable of providing accurate predictions of crop yield.

Pant et al. (2020) developed a fuzzy control system for assessing the quality and fertility of 106 soil samples in the Nainital district of Uttarakhand, India. The study focused on developing rule descriptions based on N, P, and K to evaluate soil parameters and determine their impact on soil health and fertility levels. Fuzzy logic principles were employed using Python's skfuzzy tool to create a framework that integrates various soil quality indicators and expert knowledge. Ogunleye et al (2018) proposed a fuzzy logic-based tool to offer accurate and accessible predictions of soil fertility levels in their study in Nigeria. Through data collection, preprocessing, and the formulation of fuzzy logic models incorporating linguistic variables and rules, the system evaluated input soil parameters to determine soil fertility. The inference engine computed the degree of membership for each linguistic variable, resulting in an output indicating the inferred soil fertility level. The system aimed to assist farmers, land managers, and policymakers in making informed decisions regarding soil nutrientmanagement practices by providing accurate predictions of soil fertility, ultimately contributing to enhanced agricultural productivity and sustainability in Nigeria and similar regions. Wan Yahya et al. (2021) explored the application of fuzzy logic in predicting the micronutrient requirements of Harumanis mango across various growth stages. They developed a predictive model based on 27 fuzzy rules of N, P, K present as input and N, P, K needed as output using MatLab. Through experimentation and validation, they demonstrate the efficacy of their fuzzy logic-based approach in providing reliable predictions of micronutrient demand, thereby offering a valuable tool for optimizing nutrient management strategies in mango cultivation to enhance yield and quality.

Machine learning for Prediction and Recommendation System Based on Soil Nutrients

Classification is supervised machine learning that instructs machines on how to group data based on specific criteria, such as predetermined characteristics. It predicts a data point that belongs to one of the predefined classes. The prediction is based on learning from a known dataset (Kotu and Deshpande, 2019). It is a two-step process, by analyzing the attributes within the dataset to build a model with predetermined class labels and then estimate the analytical accuracy of the built-in model. Before applying classification techniques, it is crucial to perform data cleaning, data transformation, and relevance analysis to refine the dataset and optimize its suitability for accurate model training and prediction. The results of the classification models are evaluated according to its scalability, speed, predictive accuracy, robustness and interpretability (Awasthiand Bansal, 2017).

Pandith et al. (2020) explained the prediction of the Mustard crop yield model based on soil analysis of a dataset consisting of 5000 instances with 11 input parameters representing soil nutrient levels of the Jammu region by employing machine learning algorithms like K-Nearest Neighbor (KNN), Naive Bayes, Multinomial Logistic Regression (MLR), Artificial Neural Network (ANN) and Random Forest (RF). Each model's performance assessed was based on metrics such as accuracy, recall, precision, specificity and F-Score by dividing the dataset into 70:30 training and testing sets respectively.

Based on comparative analysis, KNN and RF predicted the highest accuracy of 88.67 and 94.13 percent respectively. MLR – 80.24%, ANN – 76.86% and Naive Bayes predicted the lowest accuracy of 72.33%. Bondre and Mahagaonkar (2019) designed a system to predict crop yield using machine learning algorithms such as Support Vector Machine (SVM) and Random Forest (RF) based on five years of prior agricultural data. The system also suggests appropriate fertilizers for eachspecific crop. The performance evaluation was done on precision, f1-score recall, and an average value. Yield prediction was conducted using crop yield data, nutrient information, and location data. Additionally, fertilizer recommendations were made based on fertilizer data, specific crop details, and location data. RF had good accuracy (86.35%) when compared with SVM for soil classification. The SVM algorithm exhibits 99.47% accuracy for yield prediction, while the RF algorithm's accuracy was 97.48%.

Archana and Saranya (2020) designed a comprehensive system for crop rotation, yield prediction, and forecasting along with fertilizer recommendations. The system integrated N, P, K levels, soil type, soil texture, land type, pH, and soil EC as inputs. Moreover, the system utilized temperature data to offer the most suitable crop suggestions. The proposed system was developed using voting based ensemble classifier algorithm. An ensemble classifier is a cluster of classifiers of Naive Bayes, Random Forest and Chi-square automatic interaction detection (CHAID). An output of each classifier suggests crops separately for the user given input suggests the crops with the highest vote are to use. The yield calculation for the crop suggested by the Ensemble Classifier model is computed relying on the area of the cultivation land in acres. The distance measure was applied to the provided NPK values to generate the top three alternate crop suggestions. Performance is determined based on response time using a stopwatch and accuracy metric by the formula: Number of correct predictions/ Total number of predictions made. According to the authors, the proposed crop recommendation system gives 92% accuracy.

Malik et al. (2021) performed an analytical comparison of soil characteristics for the prediction of fertility and crop productivity employing machine learning techniques K-Nearest Neighbour algorithm, Naive Bayes algorithm and Decision Trees classifier. The dataset of 1320 cases and four parameters (temperature, pH, moisture and sunlight of) potato, tomato, and chilli crops were taken for the research and implementation was conducted using Python. The visualization of data was accomplished using the Matplotlib library in Python. KNN algorithm predicted the yield by considering the Euclidean distance, with an accuracy of 91.179%. The naive Bayes algorithm predicted using the Bayes theorem, with a relatively lower accuracy of 76.426%. Decision Trees predicted the yield through the Gini index, with the utmost prediction of 95.361%. However, the soil fertility prediction work was carried out by Rajamanickam and Savitha (2021), by employing Decision Tree (DT), K-Nearest Neighbour (KNN), and Support Vector Machine (SVM). The dataset (pH, EC, OC, N, P, K, S, Cu, Fe, Zn, Mn) of 1000 soil samples was classified into two class labels: Ideal and NotIdeal. The dataset was split into training and testing sets with a ratio of 70:30. Implementation was done using R Tool version 3.5.3. The performance analysis was conducted using various evaluation metrics, such as mean absolute error (MSE), cross- validation, and accuracy. DT resulted in 99% accuracy with minimum MSE i.e., 0.01.

Pande et al., (2021) suggested a model proposing profitable crop options for a specific location and projecting yield based on cultivated area, GPS, and soil type. They utilized various machine learning techniques for yield projection, including ANN, SVM, Multivariate Linear Regression, Random Forest, and KNN, tested on historical datasets from Maharashtra and Karnataka states. Among these, the Random Forest algorithm demonstrated the highest accuracy of 95% for the given dataset. The proposed system incorporates a mobile phone as the end-user application, utilizing GPS for location identification. Users input their land area and soil type, enabling the system to recommend suitable crops for cultivation. Gosai et al. (2021) proposed a crop suggestion system that proposes the most suitable crop by predicting the accuracy of the future production of different crops based on various parameters (N, P, K, soil pH, humidity, temperature, and rainfall). The data sensed by the sensors was stored on the microcontroller and analyzed by Naive Bayes, Support Vector Machine, Decision Trees, Logistic Regression, Random Forest, and XGBoost. The best accuracy is achieved by XGBoost (99.31 %).

Various machine learning models used for prediction and their effectiveness for agricultural use based on soil nutrients are described in Table 2.

Table 2: Overview of prediction models and its performance for agriculture use

Focus	Methods	Performance Evaluation	Reference
Prediction of Mustard cropyield based on soil analysisusing KNN, Naive Bayes, MLR, ANN, and RF	Accuracy, Recall, Precision, Specificity, F-Score	KNN and RF had the highest accuracy (88.67% and 94.13% respectively), while Naive Bayes had the lowest(72.33%).	Pandith *et al.* (2020)
Prediction of crop yield andfertilizer recommendation using SVM and RF	Precision, Recall, F1-Score, Averag e	Random Forest outperformedSVM in soil classification (86.35% vs. 99.47% accuracy).	Bondre *et al.* (2019)
Design of a crop recommendation system using ensemble classifiers	Respons eTime, Accurac yMetric	The proposed system achieved 92% accuracy in crop recommenda tions.	Archana and Saranya (2020)
Comparative analysis of soil properties using KNN, Naive Bayes, and Decision Trees	Accuracy	KNN achieved 91.179%, Naive Bayes 76.426%, and Decision Trees 95.361% accuracy.	Malik *et al.*(2021)
Prediction of soil fertility using DT, KNN, SVM	MSE, Cross-validation, Accuracy	Decision Tree achieved 99% accuracy with the lowest MSE.	Rajamanickam and Savitha (2021)
Crop recommendation and yield prediction using ANN, SVM, MLR, RF, KNN	Accuracy	RF achieved 95% accuracy for crop recommendati on.	Pande et al.(2021)

CONFLICT OF INTEREST: None

ETHICS: Not applicable

REFERENCES

- **Ahmed, U., Lin, J.C., Srivastava, G. and Djenouri, Y. 2021.** A nutrient recommendation system for soil fertilization based on evolutionary computation. *Computers and Electronics in Agriculture.* **189**: 1-7.
- **Alfin, A.A. and Sarno, R. 2017.** Soil irrigation fuzzy estimation approach based on decision making in Sugarcane industry. In: *11th International Conference*

on Information & Communication Technology and System (ICTS), Surabaya, Indonesia, 2017, pp. 137-142.

- **Amruta, N., Maruthi, J. B., Sarika, G. and Deepika, C. 2015.** Effect of integrated nutrient management and spacing on growth and yield parameters of blackgram cv. LBG 625 (Rashmi). *The Bioscan.* **10(1)**: 193-198.
- **Archana, K. and Saranya, K.G. 2020.** Crop yield prediction, forecasting and fertilizer recommendation using voting-based ensemble classifier. *SSRG Int. J. Comput. Sci. Eng.* **7(2020)**: 1-4.
- **Arogundade, Oluwasefunmi & Atasie, C. & Misra, Sanjay & Sakpere, Aderonke & Abayomi-Alli, Olusola & Adesemowo, A.** (2021). Improved Predictive System for Soil Test Fertility Performance Using Fuzzy Rule Approach. 10.1007/978-981-16-0708-0_21. **Awasthi, N. and Bansal, A. 2017.** Application of Data Mining Classification Techniques on Soil Data using R. *International Journal of Advances in Electronics and Computer Science*. **4(2017)** 33-37.
- **Balusamy, A., Ramesh T., Choudhury, B.U., Hazarika, S., Moirangthem, P., Chanu, L.J., Chakraborty, M.R.K., Laha R. and Rajappa, J.J. 2020.** Acid soil health management for livelihood improvement. Extension bulletin no. 83. ICAR Research Complex for NEH Region, Umiam, Meghalaya - 793103.
- **Bang, S., Bishnoi, R., Chauhan, A.S., Dixit, A.K. and Chawla, I. 2019.** Fuzzy Logic based Crop Yield Prediction using Temperature and Rainfall parameters predicted through ARMA, SARIMA, and ARMAX models. In: *Twelfth International Conference on Contemporary Computing (IC3)*, Noida, India, 2019.
- **Bondre, D.A. and Mahagaonkar, S. 2019.** Prediction of crop yield and fertilizer recommendation using machine learning algorithms. *International Journal of Engineering Applied Sciences and Technology*. **4(5)**: 371-376.
- **Choudhary, M., Dutta, S. and Mahajan, J.K. 2022.** Fuzzy Inference system for soil fertility crop prediction. *International Journal of Innovative Research in Technology*. **9(7)**: 257-260.
- **Food and Agriculture Organization 2015.** 2015 International Year of Soils. https://www.fao.org/soils-2015
- **Food and Agriculture Organization 2019.** The State of Food Security and Nutrition in the World 2019. Retrieved from http://www.fao.org/3/ca6030en/CA6030EN.pdf
- **Food and Agriculture Organization 2020**. The State of Food and Agriculture 2020. Retrieved from http://www.fao.org/3/ca9647en/CA9647EN.pdf
- **Food and Agriculture Organization 2021**. The State of Food Security and Nutrition in the World 2021. Retrieved from http://www.fao.org/3/ca9692en/CA9692EN.pdf
- **Gosai, D., Raval, C., Nayak, R., Jayswal, H. and Patel, A. 2021.** Crop Recommendation System *International Journal of Scientific & Technology Research*. **8(10)**: 1121-1125.
- **JuhiReshma, S.R., and D. John Aravindhar. 2021.** Fertilizer estimation using deep learning approach. *Natural Volatiles & Essential Oils Journal*. 5745-5752.
- **Klompenburg, Thomas, Kassahun, Ayalew, Catal, Cagatay, 2020.** Crop yield prediction using machine learning: A systematic literature review. *Computers and Electronics in Agriculture*, **Volume 177**
- **Kotu, V. and Deshpande, B. 2019.** Data Science Concepts and Practice (Second Edition). Morgan Kaufmann Publishers Cambridge. p.548.
- **Lal, R. (2015)**. Soil degradation as a reason for inadequate human nutrition. Food Security, 7(5), 981-996.
- **Liakos KG, Busato P, Moshou D, Pearson S, Bochtis D.2018** Machine Learning in Agriculture: A Review. *Sensors (Basel).* **18(8):2674**
- **Lobell, D. B., Schlenker, W., & Costa-Roberts, J. (2011).** Climate trends and global crop production since 1980. Science, 333(6042), 616-620.
- **Malik, P., Sengupta, S. and Jadon, J.S. 2021.** Comparative analysis of soil properties to predict fertility and crop yield using machine learning algorithms. In: *2021 11th International Conference on Cloud Computing, Data Science & Engineering (Confluence)*. IEEE, 2021.
- **Mella, N.V.V.P. and Venkata, M.P. 2022.** Crop yield prediction and Fertilizer Recommendation using Voting Based Ensemble Classifier.*Journal of Engineering Sciences*. **13(8)**: 262-270.
- **Meshram, V.A., Patil, K., Meshram, V.V., Hanchate, D.B., &Ramkteke, S.D.(2021).** Machine learning in agriculture domain: A state-of-art survey. *Artificial Intelligence in the Life Sciences*1.
- **Ogunleye GO, Fashoto SG, Mashwama P, Arekete SA, Olaniyan OM, Omodunbi BA. 2018** Fuzzy Logic Tool to Forecast Soil Fertility in Nigeria. *Scientific World Journal*, Volume 2018
- **Onashoga, A., Ojesanmi, O., Johnson, F., Femi, E.A.2018.** A fuzzy-based decision support system for soil selection in olericulture. *Journal of Agricultural Informatics.* **9(3)**: 65-77.
- **Pande, S.M., Ramesh, P.K., Anmol, A., Aishwarya, B.R., Rohilla, K. and Shaurya,**
- **K. 2021.** Crop Recommender System Using Machine Learning Approach. In: *15th International Conference on Computing Methodologies and Communication (ICCMC)*, Erode, India, 2021, pp.1066-1071
- **Pandey, A., Patra, A. K., & Singh, D. (2016).** Soil nutrient status and crop yields in India: Importance of micro-nutrients. International Journal of Plant & Soil Science, 11(2),1-14.
- **Pandith, V., Kour, H., Singh, S., Manhas, J. and Sharma, V. 2020.** Performance evaluation of machine learning techniques for mustard crop yield prediction from soil analysis. *Journal of Scientific Research.* **64(2)**: 394-398.
- **Pant, H., Chandra, L., Bhatt, A., Pant, J. and Singh, M.K. 2020.** Rule Descriptions for Soil Quality and Soil Fertility Assessment using Fuzzy Control System. *International Journal of Recent Technology and Engineering.* **8(6)**: 1341-1346.
- **Paul, M., Vishwakarma, S.K. and Ashok Verma, A. 2015.** Analysis of soil behavior and prediction of crop yield using data mining approach. In: *International Conference on Computational Intelligence and Communication Networks (CICN)*. 766-771.
- **Prabakaran, G., Vaithiyanathan, D. and Ganesan, M. 2018.** Fuzzy decision support system for improving the crop productivity and efficient use of fertilizers. *Computers and Electronics in Agriculture.* **150 (2018)**: 88-97.
- **Rajamanickam, J. and Savitha D.M. 2021.** Predictive model construction for prediction of soil fertility using decision tree machine learning algorithm." *INFOCOMP Journal of Computer Science.* **20(1)**: 49-55.
- **Reddy, A. A. (2019)**. The soil health card Scheme in India: Lessons learned and challenges for replication in other developing countries. Journal of Natural Resources Policy Research, 9(2), 124-156.
- **Sarker, I.H. 2021.**Machine Learning: Algorithms, Real-World Applications and Research Directions. *SN COMPUT. SCI.* **2, 160.**
- **Savary, S., Willocquet, L., Pethybridge, S. J., Esker, P., McRoberts, N., & Nelson, A. (2019)**. The global burden of pathogens and pests on major food crops.

Nature Ecology &Evolution, 3(3), 430-439.

- **Sharma, A., Jain, A., Gupta, P. and Vinay Chowdary, V. 2020.** Machine learning applications for precision agriculture: A comprehensive review. *IEEE Access.* **9(2020)**: 4843-4873.
- **Sharma, Neha, Sharma, Reecha, Jindal, Neeru, 2021.**Machine Learning and Deep Learning Applications-A Vision. *Global Transitions Proceedings*,**Volume 2, Issue 1**.
- **Singh, D. K., Singh, A. K., Singh, S. K., Singh, M. and Srivastava, O. P. 2015.** Effect of balanced nutrition on yield and nutrient uptake of pea (*Pisumstivum* L.) under Indo- Gangetic plains of India. *The Bioscan.*10(3)**: 1245-1249.
- **Smith, M. R., Reis Hodecker, B. E., Fuentes, D., & Merchant, A.** (2022). Investigating Nutrient Supply Effects on Plant Growth and Seed Nutrient Content in Common Bean. *Plants (Basel, Switzerland)*, *11*(6), 737.
- **Tscharntke, T., Clough, Y., Wanger, T. C., Jackson, L., Motzke, I., Perfecto, I., Vandermeer, J. & Whitbread, A.** (2012). Global food security, biodiversity conservation and the future of agricultural intensification. Biological Conservation, 151(1), 53-59.
- **Wan Yahya, Wan Mohd Nooriman & Abdullah, Abu Hassan & Abdul Rahim, Norasmadi& Tan, Erdy. (2021).** Fuzzy logic based prediction of micronutrients demand for harumanis mango growth cycles. Journal of Physics: Conference Series. 2107