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Deep Learning for Soil Nutrient Prediction and Strategic Crop Recommendations: An Analytic Perspective

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ABSTRACT

Agriculture has been a vital sector for the majority of people, especially in countries like India. However, the increasing need for food production has led to intensive farming practices that have resulted in the deterioration of soil quality. This deterioration in soil quality poses significant challenges to both agricultural productivity and environmental sustainability. To address these challenges, advanced soil nutrient prediction systems that utilize machine learning and deep learning techniques are being developed. These advanced soil nutrient prediction systems utilize various sources of data, such as soil parameters, plant diseases, pests, fertilizer usage, and changes in weather patterns. By mapping and analyzing these data sources, machine learning algorithms can accurately predict the distribution of soil nutrients and other properties essential for precise agricultural practices. A previous study compared machine learning algorithms like SVM and Random Forest with deep learning algorithms CNN and LSTM for predicting crop yields. The most appropriate model is a significant challenge, but several studies have evaluated recommendation system models using deep machine learning techniques. Deep learning models attain accuracy above 90%, while many ML models achieve rates between 90% and 93%. Furthermore, the research seeks to propose specific crop suggestions grounded in soil nutrients for precision agriculture to enhance crop productivity.

INTRODUCTION

The nutrients originate from the mineral component of the soil. Macronutrients, including oxygen, magnesium, nitrogen, oxygen, calcium, carbon, potassium, hydrogen, sulfur, and phosphorus, along with micronutrients like molybdenum, iron, boron, copper, manganese, zinc, and chlorine, are vital elements for crop growth. Minerals exist in the soil based on the pH indicators. Tobiszewski & Vakh (2023) analyzed one of the most essential elements for farming is soil. Regular soil analysis is the foundation of a valuable farming strategy for regulating soil quality. This technique aims to determine the precise amount of nutrients or other chemical, physical, and biological soil qualities. Keshavarzi et al. (2022) examined Soil nutrients, both micronutrients and macronutrients, which should be at optimum levels for agricultural production. Chana et al. (2023) suggested that crops require a favorable ratio of soil nutrients and weather conditions to grow well. Fertilizers assist in achieving high yields. Schut and Reymann (2023) have determined that the RC-KP model is a new approach that accurately predicts the short-term and long-term effects of fertilizers in crop rotations for nitrogen, phosphorus, and potassium. Khan et al. (2022) proposed the main challenge in creating a real-time and context-aware fertilizer recommendation system lies in the complexity of accurately mapping soil fertility in real-time. Kashyap & Kumar (2021) emphasized the importance of maintaining adequate soil moisture levels to support various biophysical processes. It includes seed germination, plant growth, nutrient cycling, and the preservation of soil biodiversity. Keesstra et al. (2016) conducted a study to explore the significance of soil moisture in the hydrological cycle, which plays a crucial role in regulating runoff levels, vegetation production, and evapotranspiration. It also directly affects agricultural drought, uncertainty in crop yields, and food security conditions. Chandra et al. (2023) examined Soil fertility not only enhances vegetation restoration but also promotes the development of a carbon-neutral ecosystem. It is a crucial factor for plant nutrition and plays a vital role in maximizing crop productivity. Elbasiouny et al. (2022) proposed Climatic conditions have an impact on both plant productivity and soil nutrition. In their study, Sharma et al. (2021) discussed how the depletion of essential macro and micronutrients in soils occurs as a result of erosion, which is detrimental to plant growth, leading to decreased fertility with increasing soil depth. The availability of nutrients is influenced by several factors, including pH, organic matter content, temperature, and soil moisture. In recent decades, there have been significant advancements in AI, leading to the development of various Machine Learning methods such as RF, SVM, and ANN (Ahmad et al. 2010). These methods offer new possibilities for retrieving soil moisture from satellite data. Babalola et al. (2023) presented soil surface texture has an impact on different soil properties and water-holding capacities these classifications do not accurately represent the challenges found in real-world conditions. To address this issue, the author suggests using a CNN model to classify soil images taken under Uncontrolled Field Conditions. Durai & Shamili (2022) suggested DL and ML algorithms play a crucial role in agriculture. They are primarily used to recommend crops based on weather parameters, suggest nutrient requirements, and determine the Degree Days. Kouadio et al. (2018) proposed an Extreme Learning Machine model that utilizes both MLR and RF to analyze soil fertility properties and produce a precise estimation of Robusta coffee yield. Kumar et al. (2023) employed a DL model called Deep Capsule Autoencoder with SoftMax Regression to predict the growth of crops such as sugarcane, rice, and wheat.

Deep learning algorithms suggest crops to farmers by gathering and processing the dataset, eliminating missing and duplicate data before training. Soil fertility plays a crucial role in vegetation regeneration and creating a carbon-neutral ecosystem. Fig. 1 shows crop recommendation system architecture for the qualities of the soil are determined based on its pH, macronutrients, micronutrients, climate, and geography. Using various input parameters with SVM, k-NN, RF, and Ensemble Techniques helps identify suitable crops for agriculture-fit soil. To select the most appropriate algorithm for crop recommendation, deep learning models utilize performance metrics such as F1 and accuracy scores. Machine Learning models serve as decision-support tools for predicting suitable crops in precision farming. The research aims to investigate soil nutrients in different soil types to help farmers choose the right crop for their land. ML and DL models will focus on examining primary soil nutrients, surveying minerals and fertilizers usage, predicting soil properties, identifying degradation of soil fertility, overviewing current issues in nutrient systems development, and finding suitable algorithms for crop recommendation.

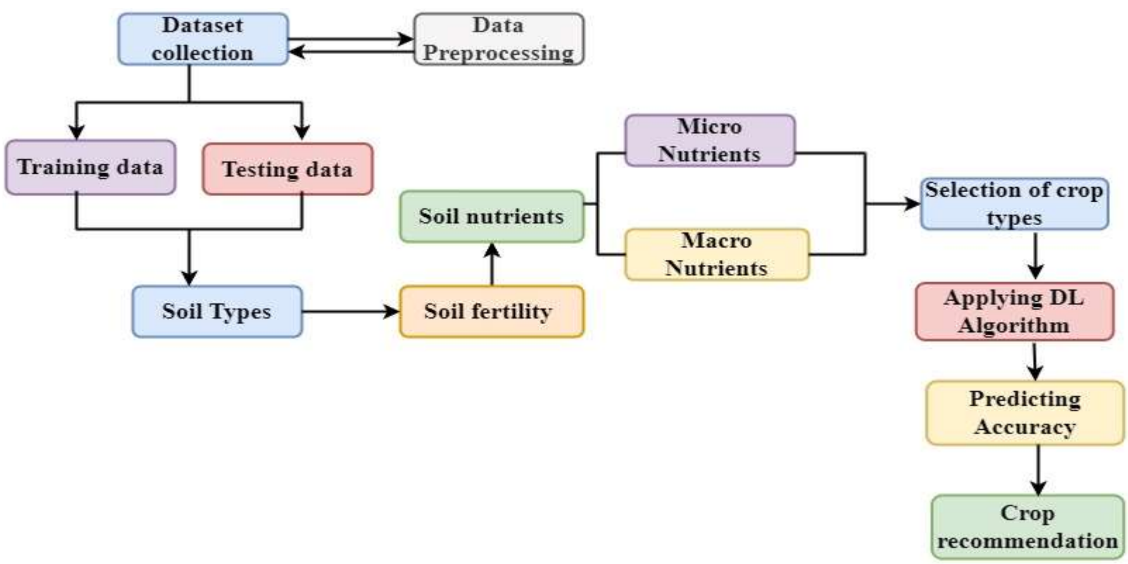

Fig. 1: Crop recommendation system architecture.

Structured Literature Review

Publications were selected using a search idiom to choose from scholarly literature. Various sources, including Elsevier, Springer Nature, Scopus, Google Scholar, IEEE Access, and MDPI, were utilized. After careful screening, 93 articles meeting PRISMA criteria for systematic reviews and meta-analyses were preferred. Fig. 2 illustrates the detailed flowchart of the systematic literature survey on publication analysis using the Prisma model.

Ahmed et al. (2021) improved the genetic algorithm and proposed nutrient recommendations based on time-series sensor data that are widely used in agricultural fertilizers to support healthy crop growth and promote optimal crop development through efficient root nutrition N, P, K. Lee et al. (2019) used deep learning to diagnose crop disease from crop leaf photos, the research suggests a self-predictable crop yield platform to forecast a farm's yearly production. A crop yield prediction module uses environmental data and disease information from the Crop Disease Diagnosis Module. Soil information was predicted by Kumara Perumal et al. (2022) using soil data, which included quantitative properties such as CEC, OC, and pH, as well as qualitative properties like order, suborder, and great group. The generated digital soil maps help farmers increase productivity by maximizing nutrient use and maintaining the agricultural ecosystem's sustainability. Dash et al. (2021) proposed ML algorithms such as SVM and DT, are used to distinguish the crop type and micronutrients for crop prediction**.** The soil pH, temperature, humidity, sunlight, and Rainfall influence the environmental factors and Crop growth. Gupta et al. (2022) examined farmers can precisely estimate crop yields throughout the growing season since it allows them to predict market prices and limits crop losses. The farmers are assisted through AI technology in making informed decisions about suggested crops to grow on their land**.** According to Gosai et al. (2021), several models, including Logistic Regression, Support Vector Machine, Naive Bayes, Decision Tree, Random Forest, and XGboost, have been suggested for cultivating multiple Indian crops. Sensors for measuring pH, temperature, humidity, NPK nutrients, soil moisture, and appropriate crop forecasts were created by Jejurkar Siddhi et al. (2021). Also decreases the risk of soil decay. Kimetu et al. (2008) used Artificial Intelligence to predict the soil properties offering suitable crop production. Fertilizers in agriculture are used for farm profitability and environmental

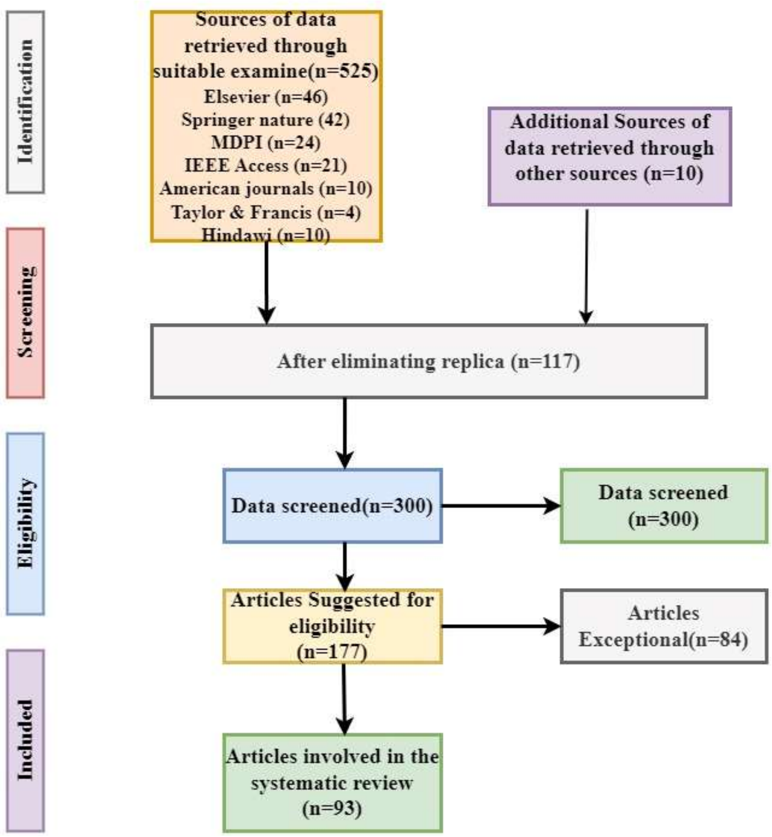

Fig. 2: Prisma Model.

protection. It computes complex nutrient deficiency and crop growth with the progress of soil fertility. Lacasta et al. (2018) found pests in crops that reduce crop yields without endangering human or environmental survival; as a result, governments have developed appropriate products and protocols of use. Finding pests and the right treatments is made easier by the established suggestion system. Principal component analysis and Sentinel 2 imagery were utilized by Singha et al. (2023) to forecast soil nutrients through Partial Least-Squares Regression and Support vector Machines Regression models, to optimize laboratory expenses. Amudha & Brindha (2022) explored the application of machine learning and deep learning techniques in identifying plant diseases and infections in various crops. The proposed model demonstrates strong computational performance and reduces processing time during the learning process. Archana & Kumar (2023) analyzed various deep learning algorithms, such as RNN, CNN, MLP, and LSTM, to predict crop yields in the agricultural sector. The CNN method proves to be highly effective in object detection and image classification, while the LSTM can capture complex and nonlinear relationships within the data. Both CNN and LSTM are valuable tools for accurately estimating agricultural yields. Sudhakar & Priya (2023) used computer vision technologies to improve crop health and productivity. These technologies were used to assess crop nutrient levels and identify any deficiencies. Techniques such as remote sensing, machine learning, and deep learning were employed to identify nutrient deficiencies in the crops.

Analysis of Soil Composition and Characteristics

Prakash et al. (2017) examined the soil dataset that was efficiently classified by utilizing classification algorithms such as ANN and SVM. These algorithms focused on various soil conditions, including fertility, depth, acidity, alkalinity, electrical conductivity, organic carbon, nitrogen, phosphorus, potassium, water-holding capacity, and porosity. John et al. (2020) highlighted the importance of analyzing SOC as an essential indicator of soil quality and fertility. They emphasized the need to understand its spatial distribution and the factors that influence it to achieve efficient and sustainable soil nutrient management using ANN, SVM, Cubist regression, RF, and MLR. Suchithra & Pai (2020) analyzed soil fertility on a village-by-village basis to identify and address nutrient deficiencies in soil, such as potassium, boron, organic carbon, and phosphorus. Senapaty et al. (2023) designed an IoT SNA- CR crop recommendation model for soil nutrient classification, minimized the use of fertilizers, and maximized productivity. Chandrappa et al. (2023) proposed statistical ML models, such as SVR, LR, and LSTM, to predict soil moisture data in multi-depth, using seasonal and non-seasonal.

Assessment of Soil Fertility: Macronutrients and Micronutrients

Kaya & Basayigit (2022) stated that agricultural production relies on plants receiving the optimal amount of nutrients. These nutrients can be classified into macronutrients and micronutrients. Table 1 is used to differentiate ML and DL algorithm and their performance metrics using feature selection and utilization of different data sets.

Crop Recommendation Framework

The comparative analysis of supervised learning methods, including SVM, DT, GNB, and Xgboost, models was conducted by Lad et al. (2022) to enhance agricultural productivity and provide crop suggestions using soil attributes. Thilakarathne et al. (2022) Developed a cloud-based crop recommendation platform for assisting farmers in crop selection using various ML algorithms such as SVM, KNN, RF, XGBoost, and DT. Wankhade & Raut (2024) proposed a novel model called Efficient Deep Learning with Attention Mechanism Model, which aims to predict crop yields accurately using soil moisture and texture. BSFFS is used for extracting the features of a Bi-LSTM. Global Attention Mechanism is employed to predict the crop. Hossain et al. (2023) utilized a machine-learning approach to suggest appropriate crops by analyzing the levels of N, P, K, temperature, pH, humidity, and rainfall. They employed various algorithms, including DT, RFR, LR, K-NN, NN, SVM, and XGBoost. Kusuma Sri et al. (2023) suggested stacking LR, SVM, and NB algorithms into Gaussian Naive Bayes to select the most suitable crop based on soil nutrients and weather conditions. Gao et al. (2023) used RF and SVM to classify crops and optimize crop fields using Landsat 8 multispectral bands. Deshmukh et al. (2022) suggested machine learning techniques were used to recommend the top three crops based on soil and weather conditions. The goal of this research was to enhance soil quality, promote better crop growth, and assist farmers in reducing financial losses while increasing productivity. Varshitha & Choudhary (2022) analyzed to help farmers predict the most suitable crop for their soil using deep learning techniques, IoT elements, and deep neural networks. Predicting soil fertility and determining the suitable crops for meeting nutritional requirements includes soil factors, pH, organic carbon content, and NPK. Elavarasan & Vincent (2020) created a Q-learning network to predict crop yield using input parameters and reinforcement learning with parametric features and a threshold. Manjula & Djodiltachoumy (2022) used Gated Recurrent Units for crop-recommended prediction in evaluating trained and tested data to forecast crop production. In their study, Venkata

Table 1: Methods of soil fertility and crop optimization using machine and deep learning techniques.

S. No.	Title/Author	Soil/Crop recommendation / Feature Selection/Method ML/DL	Limitations of the existing system	Dataset	Performance Metrics
1.	Reshma and Aravindhar (2022)	analyze soil nutrients/Soil fertility/MLP, SVM, and DT	Overfitting and Underfitting, Need for Hybrid Models.	Southernmost region of Tamil Nadu.	Accuracies 94%.
2.	He et al. (2007)	To calculate pH level and soil nutrients/N, P, K, OM, and pH / NIR spectroscopy and PCA/PLS	it is not effective for predicting phosphorus (P) and potassium (K) levels.	From the field, 165 soil samples were collected.	Correlation Coefficient: 0.93 for N, 0.93 for OM, and 0.91 for pH.
3.	Wang et al. (2015)	To predict macronutrient contents, pH value, and organic matter content/N, P, K, OM and pH/VIS/NIR, PCR, MPA FT-NIR	Poor Prediction for Certain Nutrients, Volatilization Issues.	Longkang Farm, Bengbu City	Using VIS/NIR spectrometer predicting OM and pH values better.
4.	Arisandy et al. (2022)	Soil micronutrients/N, P, K/RF, GB, DNN, PLS	preprocessing methods and spectrometer differences can significantly affect the results.	Spectroscopic data was obtained from 54 datasets.	Accuracy 91.88%
5.	Peng et al. (2019)	Soil nutrients/TN, TP, TK/ PLSR, BPNN, and GA-BPNN	To improve the estimation accuracy of soil nutrient contents.	Guangdong, China	RRMSE value of 20.37%
6.	Swapna et al. (2020)	soil nutrients and pH values. / pH, OC, EC, NPK, Cu, Fe Mn, Mg S, Br/PCA, Regression analysis techniques	Insufficient amounts of any one micronutrient in the soil can restrict and interfere with a plant's ability to grow	agricultural department.	In comparison to other soil nutrients in this area, N and K were naturally high.
7.	Sirsat et al. (2018)	Soil nutrients and fertility/OC, P2O5, Fe, Mn, Zn./Regression methods SVR, RF, PLS, bagging and boosting.	It is critical to improve the quality of the soil and maintain appropriate levels of various nutrients.	Marathwada region	Accuracy 97.63%
8.	Escorcia-Gutierrez et al. (2022)	Designed Soil nutrients/P, K, OC, and B/DL, GRU, DBN, Bi-LSTM,	an effective tool is needed to determine the right amount of soil nutrients based on crop requirements and fertility levels.	Samples from individual farmers.	Accuracy 0.9497
9.	Nyakuri et al. 2022)	Soil on Climatic conditions/pH, EC, N, Cu, Fe/IoT architecture	to enhance the agriculture activities to satisfy the need to increase farm productivity	Real-time data	Accuracy 0.963
10.	Ma et al. (2022)	Soil nutrients/Soil properties (e.g., pH, total nitrogen, soc)/ DT, RF, SVM, and NN	intercropping is known to improve soil nutrients and crop productivity, and microbes mediate the effects on belowground processes.	Soil ecosystem multifunctionality.	Phosphorus 87% and 16%
11.	Ahado et al. (2023)	Forest soil/P, K, Ca, Mg, Cu, F and Pb/MLAs, SGB -RK, and CUB_RK	soil problems are caused by the composition of and the presence or absence of particular materials. This will reduce agricultural land productivity.	An auxiliary	Cubist_ RK
12.	Blesslin Sheeba et al. (2022)	Micronutrients in soil/B, OC, K, P, and pH./Extreme learning method (ELM)	the need for more advanced and accurate systems to manage soil quality and crop production effectively.	Mulberry cultivation districts	K-3-5%, N-80%, and S-75%.
13.	Thapa et al. (2021)	Micronutrients/Fe, B, Mn, Zn, Cu, Mo, Cl, and Ni/Soil and foliar applications, SOM	To explore the potential for using micronutrients, we reviewed the literature evaluating the effect of micronutrients on soybean production	Not Defined	Fe - 1.91
14.	Dasgupta et al. (2023)	Soil micronutrient/Zn and Fe/ Hybrid ensemble model	investigate the potential of micronutrients to evaluate their effect on soybean production.	Not Defined	R2: Zn, Fe .0.52,0.63

Naresh & Kullayamma (2024) introduced an innovative deep-learning approach that utilizes the Concurrent Excited Gated Recurrent Unit and Deep Learning to automatically recommend crops based on soil, fertilizers, and climatic conditions. Ezhilarasi & Rekha (2022) focused on increasing farmers' profit through crop recommendations in towns and villages, using fuzzy ant clustering and association rule mining for crops.

MATERIALS AND METHODS

Advanced Machine Learning Classifiers for Soil Nutrient Analysis and Crop Recommendation Systems

The Supervised and unsupervised learning techniques encompass a variety of methods, such as decision tree classifiers, Bayesian classifiers, artificial neural networks, nearest neighbor classifiers, random forests, and support vector machines for uncovering patterns being studied. Additionally, ML models, including DT, KNN, and multivariate logistic regression have been introduced for forecasting the annual crop yields in certain West African countries with promising accuracy. Finally, a system was proposed to predict crop yields and recommend fertilizer using random forest and logistic regression algorithms (Jagtap et al. 2022, Cedric et al. 2022, Devan et al. 2023).

Fig. 3 shows crop prediction performed using innumerable machine learning algorithms. Several studies have proposed various machine learning algorithms for crop prediction, including Decision Trees, Multiple Linear Regression, Neural networks, XGBoost, SVM, KNN, and Naïve Bayes. The authors proposed crop recommendations based on some variables, including rainfall, temperature, humidity, N, P, and K. Also, they analyzed soil moisture using Soil Moisture Active Passive brightness temperature and performed crop recommendations utilizing the Internet of Things technology, along with the Message Queuing Telemetry Transport protocol and Random Forest algorithm.

These models achieved high accuracy rates in predicting rainfall, suitable crops, and soil classification. Additionally, ensemble models such as XGBoost and LightGBM were found to outperform others with an impressive 99.32% accuracy (Mahendra et al. 2020, Patil et al. 2020, Yange et al. 2020, Rahman et al. 2018, Raja et al. 2022, Padmapriya & Sasilatha 2023, Kumar et al. 2023, Tong et al. 2020, Rao et al. 2022, Dey et al. 2024, Nti et al. 2023).

Deep Learning Approaches for Enhanced Soil Nutrient Detection and Crop Recommendation Models

An Artificial Neural Network is a network of interconnected layers of nodes or neurons that mimics the neural architecture of the human brain. After processing input, these nodes train themselves to modify the connection strengths (weights) to gain knowledge from the data. This enables the network to recognize patterns, predict outcomes, and handle various machine learning and artificial intelligence tasks. Studies have shown that using the ANN approach aligned with deep learning architecture outperforms other methods in identifying crops most likely to thrive in fertile soil and forecasting crop yields with high accuracy. When it comes to classifying soil and determining agricultural yield, a variety of ML techniques are utilized, including ANN, MLP, RF NB, SVM, and LR (Yadav et al. 2021, Gopal & Bhargavi 2019). A convolutional neural network is a powerful tool for image recognition because it excels at recognizing patterns, but it requires vast amounts of labeled data. ML techniques developed by Nevavuori et al. (2019) rely on yield mapping equipment not widely used among farmers. Convolutional Neural Networks have shown promising results in image

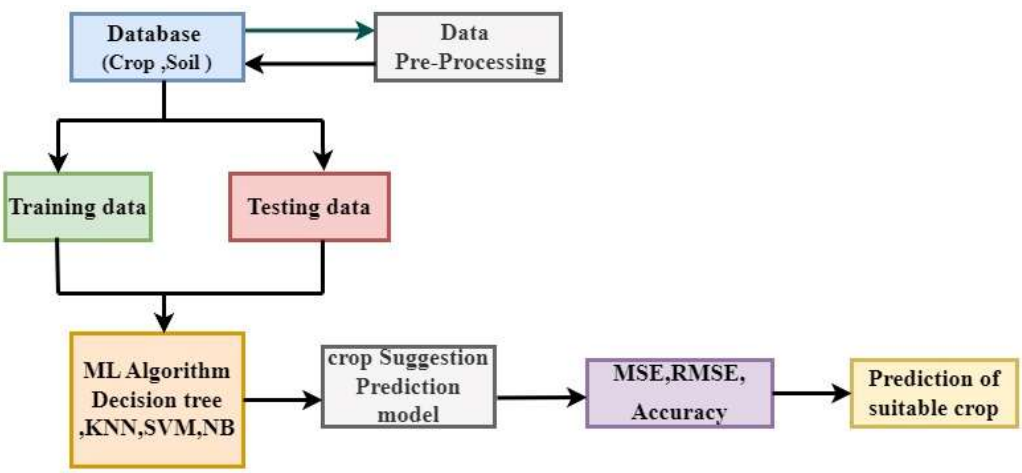

Fig. 3: Crop prediction using innumerable Machine Learning algorithms.

classification but present challenges in building crop yield forecast models, as highlighted by Xu et al. (2022). Laser-induced breakdown spectroscopy encounters reduced accuracy and stability in spectrum analysis due to soil heterogeneity; addressing this issue led to the utilization of non-pre-processed LIBS spectra for predicting soil type using CNN. A deep neural network consists of several layers positioned between the input and output layers. It shares common components such as neurons, synapses, weights, biases, and functions with other types of neural networks. This type of network can be trained like other machine learning algorithms. A special approach using deep neural networks is suggested for Predicting future crop yields by using historical yield data and greenhouse environmental information such as temperature, humidity, radiation, and CO_2 concentration (Gong et al. 2021). Recurrent neural networks belong to one of the two primary categories of artificial neural networks, distinguished by how information is transmitted between their layers. The term "convolutional neural network" describes networks with a finite impulse response, while "recurrent neural network" encompasses those with an infinite impulse response. Both types of networks exhibit temporal dynamic behavior. Sun et al. (2020) developed the Long Short-Term Memory, a widely utilized recurrent neural network architecture in Deep Learning. LSTM is known for its effectiveness in capturing long-term dependencies and is particularly well-suited for sequence prediction. Suebsombut et al. (2021) proposed an LSTM model to predict soil moisture values based on data from multiple sensors, while Kim et al. (2022) applied an LSTM model to reduce noise in agricultural sensors within a large-scale aquaponics system compared to traditional filtering approaches like Kalman and moving average filters. A densely interconnected network consists of multiple layers and utilizes combinations of neurons to transform input dimensions into the desired dimension. This allows outputs from certain neurons to serve as inputs for other neurons. Several studies have recommended using multilayer perceptron neural networks for data mining in agriculture, with the use of sigmoid and hyperbolic tangent activation functions being common. Techniques like machine learning have been suggested for crop recommendation to increase yield and quality while assisting farmers in selecting suitable crops for cultivation. These approaches outperform various algorithms, including instance-based learning with parameter k, Multi-Layer Perceptron, reduced error pruning tree, and C4.5 decision tree. Bhojani et al. (2020) and Garg and Alam (2023) proposed transfer learning refers to the utilization of a pre-trained model for a different task, which is particularly beneficial when the new task shares similarities with the original task or has limited data available. Cai et al. (2021) developed a soil nutrient extraction model by utilizing transfer learning and near-infrared spectroscopy as a response to the limitations of traditional models.

Evaluation Metrics for Assessing Soil Fertility and Crop Recommendation Systems

To predict crop yield, epochs are utilized to train the data and validate it when adjusting the base model and adding layers. Increasing the number of epochs leads to a reduction in loss details, indicating that the model is learning more as the epochs progress. The mean absolute error (MAE) determines the average magnitude of prediction errors, providing the average deviation between the expected and actual values for each forecast point. Mean absolute percentage error (MAPE), Mean squared error (MSE), and root mean squared error (RMSE) are error metrics used to assess prediction accuracy. Root absolute error (RAE) and Relative root mean squared error (RRMSE) can help farmers make decisions that increase crop yield. The RF algorithm has the lowest classification error when using RAE and RRMSE to evaluate the error measure. Crop yield is predicted to increase significantly by utilizing multi-sensor data for crop advice (Elbasi et al. 2023).

The terms "accuracy," "precision," and "recall" metrics are used to evaluate performance, including those used for crop recommendation systems. Here's what each term implies in this context:

- Accuracy: This refers to the percentage of accurate results (including both true positives and true negatives) out of all the cases that have been examined. For crop recommendations, it measures how frequently the model correctly predicts the right crop for given conditions.
- Precision: This metric represents the proportion of true positive predictions in the subset that the model predicted as positive. In crop recommendation, it is the ability of the model to only recommend a crop when it is indeed suitable.
- Recall: Recall refers to the percentage of true positives that the model correctly identifies. Sensitivity, often used interchangeably with recall, indicates the model's ability to identify all suitable conditions for a particular crop accurately.
- F1-Score: $F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$
- Sensitivity $= \frac{TP}{TP+FN}$
- Specificity $= \frac{TN}{TN+FP}$

For crop recommendation systems, these metrics are essential for accurately identifying and suggesting crops based on soil type, weather conditions, water availability, etc. They determine the effectiveness of providing reliable agricultural advice to farmers. Analyzing these metrics involves confusion matrices from classification reports or direct calculations using true positives, true negatives, false positives, and false negatives of test results.

Soil fertility index and soil pH content are critical for soil health management in agricultural research. They assess the ability of soil to provide essential nutrients to crops and measure acidity or alkalinity, which significantly affects nutrient availability and microbial activity. Analysis of variance is used to test if variations in soil management affect these factors, comparing mean levels across different practices. This information informs targeted recommendations for addressing nutrient deficiencies and advising on crop selection and fertilization plans tailored to optimize crop yield based on local conditions. Comprehensive soil testing coupled with knowledge of best management practices is essential for accurate recommendations (Jia et al. 2023, Aziz 2016, Gobbo et al. 2022).

RESULTS AND DISCUSSION

Optimized Proposed Model for Soil Fertility and Crop Recommendation Systems

Penghui et al. (2020) introduced a new hybrid model called an adaptive neuro-fuzzy inference system with mutational Salp Swarm and Grasshopper optimization algorithms, which incorporates optimization methods. They compared seven different models with the classic ANFIS model, showing that the ANFIS-MSG is particularly effective for forecasting soil temperature from a univariate air temperature scenario. Dinh et al. (2021) developed an SVM-based ML model to predict soil erosion using the L-SHADE-PWI approach, which optimizes SVM parameters through machine learning and metaheuristic optimization methods. Gopi & Karthikeyan (2024) suggested using DL and ML techniques to enhance crop productivity and predict yields. They proposed the RFOERNN-CRYP design, which combines Red Fox Optimization with Ensemble Recurrent Neural Network, along with LSTM, bidirectional LSTM, and GRU models. Choudhury et al. (2024) proposed a method to enhance prediction accuracy by integrating various classifiers based on KNN, DT, SVM, and LR into ensemble techniques using the Moth Flame Optimization algorithm for recommending crops. Shamshirband et al. (2020) demonstrated significant improvements in modeling soil temperature using SVM or MLP hybridized with Firefly optimization algorithm compared to standalone MLP or SVM models due to its effectiveness.

From the Survey, Fig. 4 shows the Crop recommendation and prediction for Agriculture using the Deep Learning Model. The crop recommendation System considers soil type, crop type, temperature, humidity, precipitation, and macro and micronutrient levels to recommend suitable crops for specific land. The proposed model uses deep learning algorithms for feature extraction and crop recommendation. The system involves three phases: The first phase - The dataset collection includes nitrogen (N), phosphorus (P), potassium (K), soil pH value, humidity, temperature, and rainfall parameters. Our goal is to help farmers choose the

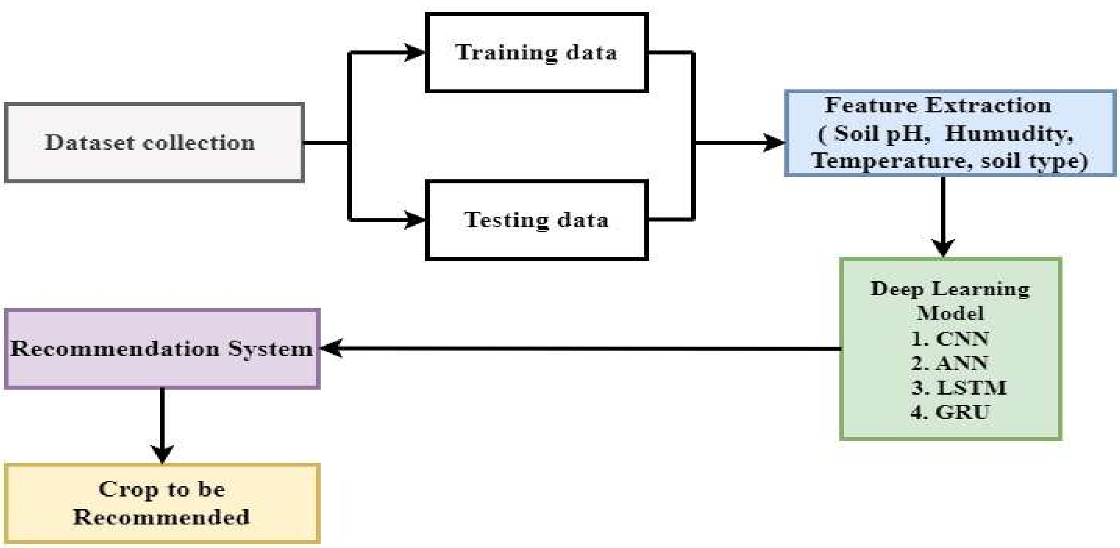

Fig. 4: Crop recommendation and prediction for Agriculture using the Deep Learning Model.

most suitable crops based on their unique circumstances and environment. We will achieve this by predicting which crops are well-suited to the factors that affect crop growth. The second phase focused on predicting soil nutrients to increase production. Different deep learning algorithms, including LSTM, CNN, ANN, and GRU, were utilized for this purpose. These algorithms helped suggest the most appropriate crop for a particular farm and predict crop yields. By considering the changes in environmental factors, this approach aimed to improve the accuracy of soil nutrient prediction and crop recommendations. Finally, in the third phase, the most suitable crop recommendation is based on using neural networks that are outperformed in the context of soil nutrient prediction and also in suitability of the crop. The referred data set is a publicly available Kaggle dataset.

The proposed model aims to improve soil nutrient prediction and crop recommendation by investigating intercropping systems, soil problems, soil nutrient deficiency, and preprocessing methods described in the limitation of the existing system in Table 1. These limitations will be significantly achieved by implementing deep learning algorithms such as ANN, CNN, LSTM, and GRU. These models will be trained with the feature selection process and analyze the various environmental factors to predict soil nutrients, recommend suitable crops, and help farmers achieve the expected yield as the best outcomes.

Interpretation of Crop Recommendation System Survey Outcome

This section examined the use of machine learning and deep learning techniques to estimate soil nutrients, analyze soil fertility, and suggest suitable crops for optimizing farmers' economic growth. Fig. 5 shows the survey analysis chart using several optimization and hybrid algorithms. In total, 93 papers were surveyed, with approximately 50 focusing on machine learning, 33 on deep learning, and 10 on optimization. Various machine learning techniques, including linear regression, random forest regression, k-nearest neighbors, support vector machines, decision trees, neural networks, and extreme gradient boosting, are recommended for crop prediction and classification in different agricultural scenarios. Regression techniques, including neural networks, deep learning, boosting lasso ridge regression, and Bayesian models, were employed to predict soil fertility and nutrient levels. Deep learning algorithms like LSTM, CNN, GRU, Bi-LSTM, DNN, SOM, RBM, DBN, GAN, RBFN MLP, and RNN were utilized to identify crop diseases from pictures of crop leaves. The GA-BPNN method was employed for mapping and estimating soil nutrients using hyperspectral techniques. For pH classification and prediction analysis, GRU, DBN, and Bi-LSTM were used, while LSTM, SVR, and LR predicted soil moisture. PCA was recommended with models such as RF, GD, DNN, and PLS applied for predicting soil minerals. LSTM, GRU, and CNN outperformed the others, resulting in high crop classification accuracy. The study aimed to test different machine learning and deep learning models to improve the accuracy of predictions. Different optimization and hybridization algorithms were utilized for tasks such as soil erosion prediction, soil temperature estimation, drought risk monitoring, crop recommendation, and crop yield estimation. Various evaluation factors were

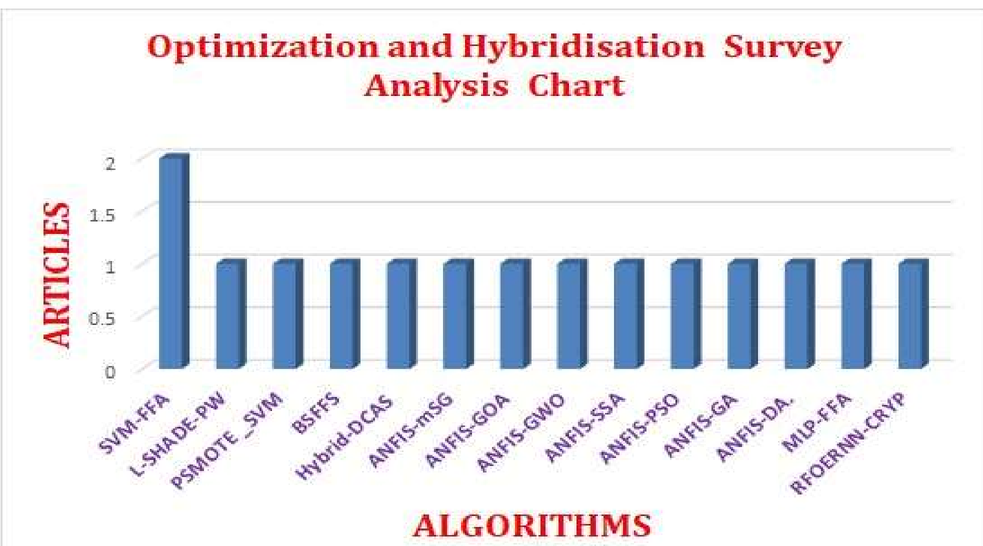

Fig. 5: Survey analysis chart.

utilized to assess the performance of different models, including precision and recall scores calculated separately for each crop type. Research publications utilized various activation functions for feature extraction and emphasized the potential of combining machine learning and deep learning techniques to optimize solutions. Extensive research on smart agriculture and intelligent soil nutrient prediction is essential for enhancing knowledge, improving prediction methods, and overcoming challenges faced by modern farmers in maximizing crop productivity.

CONCLUSIONS

In conclusion, the integration of deep learning and machine learning models into soil nutrient analysis and crop recommendation systems represents a significant advancement in precision agriculture. These models can analyze complex datasets, identify patterns, and provide accurate predictions based on a range of soil parameters, including fertility indices, pH levels, and nutrient content. The precise modeling of soil-plant interactions can be achieved through the implementation of deep learning architectures like Convolutional Neural Networks and machine learning algorithms such as Random Forests and Support Vector Machines. Advantages include improved accuracy in recommendations, real-time predictions for crop suitability and fertilization requirements, cost-effectiveness through automation, customization to regional data, and early warning systems for nutrient deficiencies. Challenges remain in terms of extensive high-quality datasets for model training/validation, interpretability of model predictions, and integrating these technologies into existing agricultural practices. Continued research is essential to refine these models further for global food security and sustainable farming practices.

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