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A Comprehensive Review on Machine Learning Approaches for Yield Prediction Using Essential Soil Nutrients

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Abstract Agriculture is the backbone of India's economy, as it is the most important factor in the country's socio-economic development. Because of the rapid expansion in human population, the "Green Revolution" introduced high yield variety (HYV) seeds, which increased crop productivity but degraded crop and soil quality. This is due to the use of excessive amounts of chemical fertilizers in HYV seeds, as well as the irrigation system utilized to grow these seeds. This stunts the growth of the crops, resulting in financial and productivity losses. Because of field surveys, traditional ways to crop production prediction will take longer, and contemporary agriculture will face certain obstacles. As a result, a comprehensive review of various crop key factors such as climatic factors, soil nutrients, production factors, and environmental factors is conducted using a variety of machine learning approaches such as Support Vector Machine, bayes classifier, decision tree, random forest, linear regression and Extreme Learning Machines. The accuracy measures such as root mean square error, coefficient of determination and mean absolute error are used for comparing the performance of the system. Based on the findings of the reviews, an intelligent and robust machine learning technique provides the optimum option for achieving (i) soil fertility, (ii) crop prediction, and (iii) yield prediction. The importance of soil variables and the amount of nutrients available in the soil for growing crops has been found, according to an examination of 51 peer-reviewed studies, to create qualitative yield prediction. Furthermore, the investigations will yield recommendations for future fertilizer research.

Keywords Green Revolution, Precision Agriculture, Machine Learning, Soil Factors, Yield Prediction

1. Introduction

Since the population is increasing rapidly, there is a huge demand for food production in most of the developing countries. The green revolution introduced in 1960s increased the production rate of the food crops through the use of high yield variety seeds, irrigation systems, chemical fertilizers, pesticides and machinery. These techniques increased the production rate but vast amounts of chemical fertilizers have depleted soil fertility, and modern irrigation facilities employed by farmers have drilled out the water table below the ground. Also, the mechanism is very expensive and out of reach for farmers, as the authors [1] concluded. The authors [2] concluded that manufacturing quality is the most important determinant of human survival. Despite the fact that present output levels may be sufficient to meet survival needs, projected agricultural food production demands will skyrocket by 2050. The primary goal of the farmers is to make as much money as possible. The yield rate increases the country's economy. Furthermore, as the authors [3] highlight, the nutrient loss will be a big concern for farmers due to artificial fertilizers and pesticides. Throughout the ages, research and innovative breakthroughs have been critical in converting our farming to be qualitative and quantitative, with precision agriculture as a crucial component. Various agricultural research has been conducted using various ML (machine learning) and DL (deep learning) methodologies to meet both crop sustainability and productivity while also conserving the ecosystem. The following are the main contributions of this article:

(a) The importance of precision agriculture for smart farming with automated resources is discussed.
(b) The foundations of machine learning are discussed, as well as their importance for agriculture in producing qualitative and quantitative food production.
(c) The performance of several machine learning algorithms in terms of yield prediction is evaluated, and how soil nutrients are an important attribute for yield prediction is examined based on their performance parameters.
(d) The research's findings are divided into three categories: soil fertility classification, crop prediction, and yield prediction.
(e) Based on this complete study, a conclusion and future research scope are offered.

Web of Science, Scopus and Google Scholar are among the databases used in the search approach. The research is based on publications published between 1985 and 2021. The researchers in the field of agriculture used machine learning techniques to review 51 papers. The authors focused their research on the issues faced by farmers on numerous databases [20][21][22][25].

Precision Agriculture

The people and the government want to improve traditional and modern agricultural methods by converting them to automated services in order to increase output. Figure 1 depicts the traditional agriculture cycle that farmers follow, as well as recent innovations. Since the global food system faces formidable challenges there is a need for investment in research to provide novel solutions [4]. Precision agriculture, a technology-enabled digital farming system, has arisen to address contemporary issues in sustainable agriculture and to obtain optimal results from exact inputs.

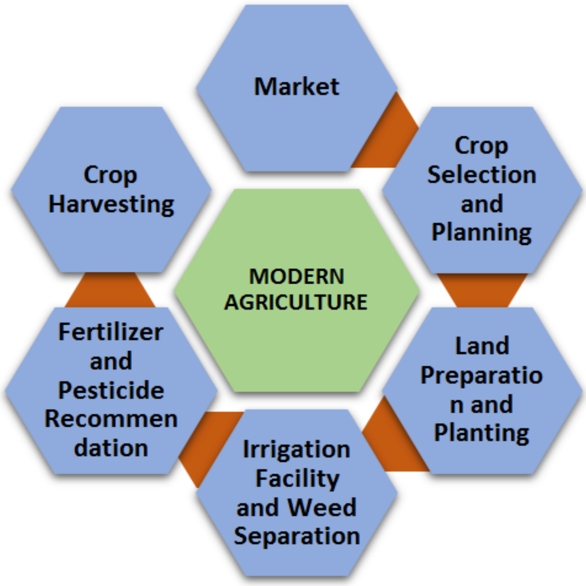

Figure 1. Traditional agriculture cycle with modern advancements

Precision agriculture will offer advice on how to automate and streamline the data collection and analysis process. The methods of precision agriculture are depicted in Figure 2. Precision agriculture is a modern approach for enhancing crop productivity using the latest technologies such as Big data analytics, the Internet of things (IoT), machine learning, deep learning, and so on, according to the researchers [4]. To assist the industry and research communities, a study is conducted on all modern techniques and procedures [5][53] engaged in smart farming.

Precision farming now demonstrates new ways to achieve balanced productivity through the use of systems assistance for agricultural concerns. Precision technologies such as global positioning systems (GPS), sensor technologies, geographic information systems (GIS), yield monitors, and precision irrigation systems are employed to complete a variety of tasks [54]. The reduction of fertilizer runoff and prevention of diseases through full autonomous aerial solutions is developed in [55]. Integration of edge computing components with ensemble models helps to provide solutions for the challenges faced by the farmers.

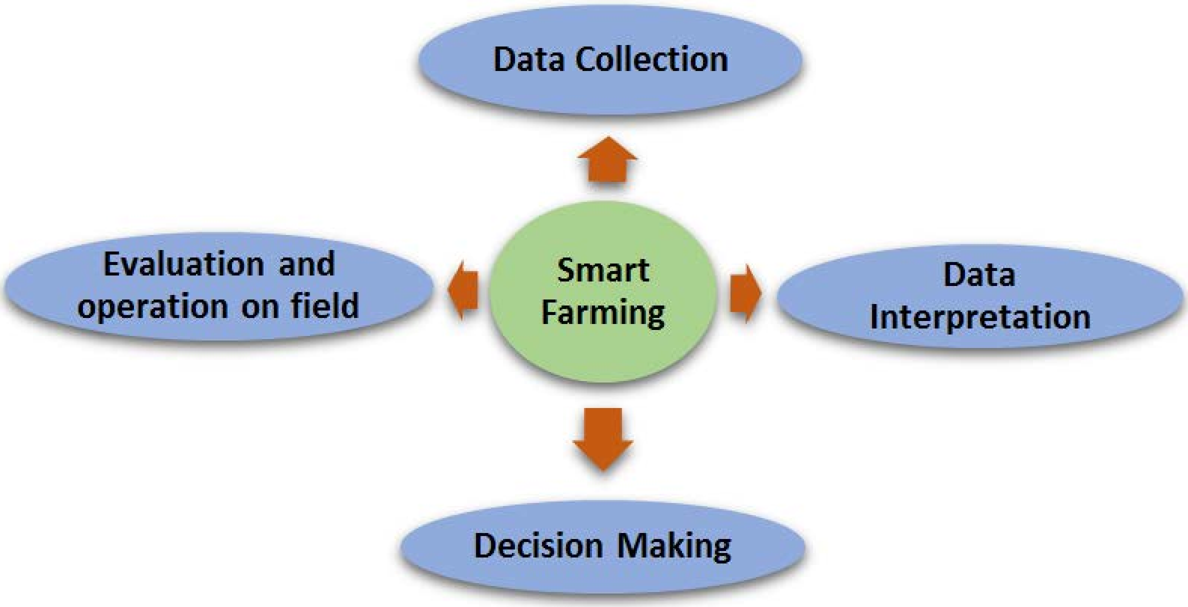

Figure 2. Precision Agriculture

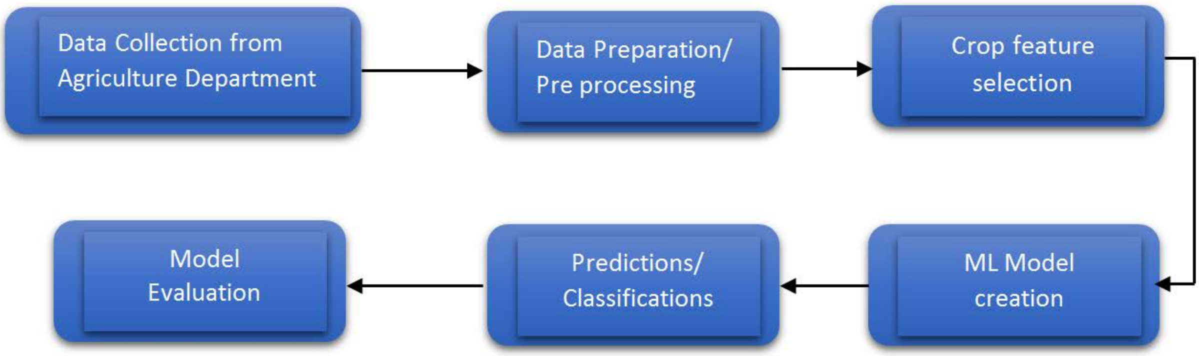

Figure 3. Machine Learning process in agriculture

However, there are various problems that the researchers will face in developing and deploying these systems. The goal of precision agriculture (PA) is to develop an intelligent support system based on various crop parameters such as type of soil, presence of nutrients in the soil, level of water, humidity, quality of seed, temperature, pH level, and so on, and since there is a need for producing surplus yield, the goal of PA is to develop an intelligent support system based on various crop parameters such as type of soil, presence of nutrients in the soil, level of water, humidity, temperature, pH level, and so on.

Role of ML and DL in Agriculture

Machine learning is the most essential branch of artificial intelligence in today's times for processing large amounts of data and solving complicated issues via experience. Initially, the authors conducted research in agriculture utilizing expert systems [6] because they provide good recommendations for solving agricultural problems with high performance, but they run into computational issues as the database grows in size. The most powerful technique preferred by most academics is ML, which can learn large databases and produce solutions automatically. ML, according to Tom Mitchell [7], is described as learning from experience with respect to some tasks with some performance measures, and then improving performance on those tasks with experience. There are four types of machine learning models: supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning. The machine learning process in agriculture is depicted in Figure 3.

As a result of large data technologies with high processing capability, machine learning has emerged in diverse sectors such as healthcare, stock predictions, surveillance systems, social studies, and Agri-technologies. In [19] 34 real-life examples are considered and concluded that machine learning and big data are becoming a hot topic in agriculture, thanks to technological advancements. As a result, a thorough examination of multiple machine learning models for yield prediction based on a variety of agricultural parameters is conducted. Several crop management apps and farming process automation are analyzed and concluded that information technology can help to increase crop output [8]. From the investigations of machine learning models and it is determined that the models employed by the applications are ANN (artificial neural networks) and SVM (support vector machines), with ANNs being used mostly for soil management and SVMs for livestock management [44].

Several factors influence crop growth and yield output, including climate, soil qualities, irrigation, and so on. Various machine learning algorithms are used for fertilizer management to improve soil quality and concluded that ML is the best tool for yield prediction [9]. Predictions using SGD (stochastic gradient descent) and ANN on Hadoop using the mahout library and compared them to KNN (K-nearest neighbor), SVM, random forest, and other methods. They employed a soil dataset and performed an experimental analysis with MAE (mean absolute error), RMSE (root mean square error), and R^2 (coefficient of discrimination) to find that SGD outperforms other approaches. As a result, machine learning plays a critical role in agriculture, providing farmers with automated solutions that enable them to make informed decisions and provide fertilizer suggestions to ensure a decent harvest.

Various technologies such as AI, the internet of things (IoT), and big data are providing ideal solutions for farmers by gathering real-time data and providing dynamic updates to meet requirements and produce quality agriculture that helps our planet and people. These technologies have a significant impact on paddy output forecast through smart cultivation. In the era of Big data in agriculture, they are widely used by researchers to provide answers based on different resources. The challenges and future developments in precision agricultural machine learning techniques are examined. It is concluded that regression algorithms work well in predicting crop yields based on soil parameters and weather [11].

Reviews of ML and DL algorithms for farm management conclude that regression models are used for soil management, CNN (convolution neural networks) algorithms are used for disease and weed management, and livestock management is done using knowledge-based smart systems that use IoT and AI tools [12].

Plant diseases and weed identification are other important components in agriculture, and most researchers are employing deep learning algorithms for early detection in order to produce quantitative production. A comprehensive overview of how DL is used in agriculture is done and an assessment of challenges in all neural are examined, concluding that DL approaches need to be improved in terms of accuracy in unstructured agriculture data [51]. Deep Learning algorithms are mostly used for disease identification and compared the results to other DL models, finding that the semi-supervised few-shot learning technique outperforms other models [52].

According to a review of various papers, ML and DL algorithms are good decision -makers for yield prediction, disease detection, and crop management using soil parameters, environmental factors, diseased images, healthy images, and other factors, and can help farmers with digital precision agriculture solutions.

2. Crop Selection and Yield Prediction

Selection of the best crop for a good harvest is the major challenge. Knowledge from experience and experts is the traditional way of selecting crops. Since the soil fertility is lost and the availability of water resources there is a vital need for automated solutions based on the dynamic changes. When the perfect crop is chosen, together with all of the necessary vitamins, tremendous yields can be expected. From the history of data collected and processed, machine learning models will propose an autonomous answer. They are good decision -makers when it comes to picking the correct crop to produce and predicting crop yields. The study gives a thorough examination of the major elements that determine crop productivity. Temperature, soil type, rainfall, humidity, pH value, nutrients, irrigation, and plant disease are only a few of them. The agricultural elements are summarized in Table 1. A complete analysis of the literature on crop yield prediction using ML and DL algorithms. The assessment criteria indicated that machine learning and deep learning models give the best answer for yield prediction, based on all publications related to yield prediction based on soil fertility index and other crop attributes. The conclusions of this thorough study on machine learning models will bring solutions to agricultural difficulties [13]. Agricultural inputs vary from one land to the next, as well as from one farmer to the next. Collecting information from a bigger area is a difficult task. A large amount of climate data from the Indian Meteorological Department is collected from chosen districts in Madhya Pradesh, India for predicting crop productivity. A user-friendly webpage for farmers is created and utilized the C4.5 algorithm to determine which meteorological component affects crop productivity, with a 75% accuracy rate [14].

Table 1. Agricultural factors and suggestions

Agriculture Factors	Suggestions for growing Major crops
Climatic factors • Temperature • Humidity • Rainfall	1. Not possible to grow in areas of extreme temperatures. • below 0ºC • above 45ºC 2. We also can't grow plants in areas of severe drought.
Land • Plains • Bottom Valleys	Not possible to cultivate on mountains.
Soil type • Sand • Silt • Clay • Gravel	Soils which are poor for cultivation. • Saline and Alkaline • Marshy and Peaty soils
Nutrients • Soil Nutrients • Added Nutrients	Lack of proper nutrients internal or external growth of the crop is spoiled.
Economic • Size of Land • Mechanization • Labour • Market	Lack of proper mechanization and good market for commodity leads to damage in production.
Environmental • Crop Disease • Pest • Weed	Reduce these factors to avoid crop damage.

Investigations on the pH value are done to evaluate the acidic and alkaline properties of the soil as well as the proportion of nutrients such as nitrogen, phosphorus, and potassium. The technology has delivered precise and accurate findings in estimating crop output and providing a suitable fertilizer ratio suggestion. They employed RF (Random Forest) and Backpropagation to estimate the error rate, which was 0.60 and 2.8 respectively [15].

Because of the drought conditions in numerous districts, rainfall is another crucial component for yield forecasts. The authors analyzed and predicted the accuracy using historical soil and rainfall data. They employed a hybrid neural network RNN (Recurrent Neural Network), which is a time series-based supervised learning approach, to determine the ideal combinations to price the production of rice crop since they used rainfall patterns. The RMSE and MAE of the output forecasts are 41.497 and 41.6, respectively [16].

The second crucial feature of yield prediction is soil categorization. SVM and RF are used for predicting crop yield for rice, wheat, soybean, and dry chilly, among other crops. The algorithm also suggests appropriate fertilizer for each crop. RF has a classification accuracy of 86.35%, while SVM has a classification accuracy of 73.75%. For yield prediction, RF accuracy is 97.48% and SVM is 99.47%. They concluded that the RF algorithm delivers good results for soil classification and the SVM algorithm produces good results for crop yield prediction [17].

Despite the fact that multiple studies have concluded that machine learning algorithms offer outstanding results for crop yield prediction, farmers still have a hurdle in selecting the appropriate crop factor based on dynamic changes. Analysis of factors such as fertilizer, pesticides, ultraviolet (UV), and land area in that region is done using SVR (support vector regression) and LR (linear regression). Crops such as wheat, corn, and others are utilized for validation, resulting in MSE values of 0.005 and R^2 values of 0.85 on average. Yield prediction is also done using attributes from the Indian government's repository, such as the state and district of the land, the season and year, and so on. To anticipate the yield, regression techniques are employed. ENet has a 4% error rate, Lasso has a 2% error rate, Kernel Ridge has a 1% error rate, and enhanced stacking regression has a 1% error rate. As a result, various authors are doing various studies in yield prediction using a variety of agricultural elements in order to provide solutions to farmers [26].

A Q-Learning reinforcement algorithm is utilized to estimate agricultural yield in the Vellore district using data like as evapotranspiration, ground frost frequency, groundwater nutrients, and others, and the system produced error rates of 0.17, 0.03, and 0.87 [35]. Farmers select crops for cultivation based on their traditional knowledge and historical experience, and predictions can be inaccurate due to natural calamities. As a result, a system based on Johnson's classifier algorithm that provides a better solution for crop selection based on numerous agricultural parameters and delivers a good accuracy of 92% for rice, groundnut, and sugarcane sites has been developed [36].

The crop yield rate is predicted using market pricing, production rate, and various government laws, and this yield rate is used to identify the best crop for cultivation. The Naive Bayes classifier predicts whether the chosen crop will provide a decent yield or not, and KNN is used to quantify similarity. The accuracy for Nave Bayes is 91.11%, and for KNN it is 75.55% [37]. Mostly RNN is used to forecast crop selection using soil type, soil fertility, soil pH, maximum temperature, minimum temperature, and rainfall, and produced RMSE for Max temp-5.002, Min temp-7.12, and Rainfall-8.17 [39].

Ensemble technique is an integration of algorithms to get the best result on a variety of parameters such as soil type and porosity, pH and NPK concentration, and so on, achieving a 99.91% accuracy [41]. Output prediction will play a crucial role for farmers in the coming years, according to the survey results summarized in Table 2, and crop yield is also dependent on correct crop selection.

Table 2. Crop Selection and yield prediction using agricultural factors.

Author	Yield Crop	Parameters	Algorithm	Accuracy Measure
S.Veenadhari et al 2014	soybean, paddy, maize, wheat	climate - rainfall, temp	C 4.5 algorithm	accuracy - 80%
Banumathi et al 2019	rice	state, district, year season, production area and levels of N, P, K	Random forest Back propagation	Random forest Error rate: 0.60 back propagation error rate: 2.8
Shruti Kulkarni et al 2018	rice	historic Soil and rainfall (31 yrs of data)	RNN	RMSE - 41.497 MAE-41.6
Devdatta A. Bondre et al 2019	rice, jowar, wheat, etc	location, soil and crop nutrients, fertilizer (5 yrs data)	Random forest SVM.	Soil Classification: SVM-73.75% RF- 86.35% Yield prediction: SVM-99.47% RF- 97.48%
Fatin Farhan Haque et al 2020	wheat, soybean and corn	water, ultraviolet (UV), pesticides, fertilizer and land area	linear regression Support Vector Regression	MSE - 0.005 R^2 - 0.85
Potnuru Sai Nishant et al 2020	cereals, paddy, nuts, tea, vegetables, etc.	state, district, season, area, crop and year	Kernel Ridge Lasso ENet algorithms	Error rate: ENet - 4%, Lasso - 2%, KernelRidge-1%
Dhivya Elavarasan 2020	paddy	evapotranspiration, ground frost frequency, groundwater nutrients, etc.	Deep reinforcement learning	RMSE - 0.17 MSE-0.03 R^2 – 0.87
Deepa et al 2019	paddy, groundnut and sugarcane	soil, water, season, farmers input, support and infrastructure.	Johnson's Classifier	Accuracy- 92%
Ramesh Medar et al 2019	rice, wheat	market price, production rate and the different government policies.	Naive bayes K-Nearest neighbour	Naive Bayes – 91.11% K-Nearest neighbour-75.55%
Sonal Jain et al 2020	rice, maize and red gram	soil type, soil fertility, soil pH, maximum temperature, minimum temperature, rainfall	RNN Random forest	RMSE Max temp- 5.002 Min temp-7.12 Rainfall-8.17
Nidhi H Kulkarni et al 2018	rice, cotton, sugarcane, wheat.	soil type and porosity, pH, NPK, rainfall, temperature, and Sowing season	Ensemble technique	Ensemble technique Accuracy – 99.91

3. Essential Soil Nutrients for Yield Prediction

The investigation of many agricultural parameters for forecasting crop yield utilizing several machine learning models for crop cultivation, as stated by several authors [13]-[18], points the research in the direction of qualitative yield prediction. The quality of crop output is determined by how rich the soil is for farming, which is also the most crucial entity for farmers to cultivate. The authors gathered information from a variety of government websites [20][21][22][25]. Soil nutrient statistics from the Department of Agriculture are collected from numerous areas across Tamil Nadu for predicting the yield of the crop. When there is a shortfall in any of the required nutrients that are not available in the soil in an optimal range, the plant's growth is hampered. Plants require 16 basic nutrients in order to thrive and complete their life cycle. Every plant absorbs Carbon (C) from the air, as well as Hydrogen (H) and Oxygen (O) from the water. The soil provides the majority of the other 13 nutrients. These are the essential components for rice plants to complete numerous metabolic tasks in one form or another [30]. The nutrients' mobility and non-mobility are listed below:

(1) N, P, K and Mg are highly mobile.
(2) Zn and Mo are moderately mobile.
(3) S, Fe, Cu, Mn and Cl are less mobile.
(4) Ca and B are immobile.

Similarly, the toxicity of the elements is also the most important symptom to be monitored because they appear first in the lower leaves.

Table 3. Essential crop nutrients with functions and deficiency [12][21][30].

<table>
<tr><th colspan="6">Non-Mineral elements</th></tr>
<tr><th colspan="2">Element</th><th>Symbol</th><th>Primary form</th><th colspan="2">Functions</th></tr>
<tr><td colspan="2">Carbon</td><td>C</td><td>$CO_2(g)$</td><td colspan="2" rowspan="3">Carbon content is absorbed from the air
Hydrogen and oxygen are absorbed from water</td></tr>
<tr><td colspan="2">Hydrogen</td><td>H</td><td>$H_2O(l)$, H^+</td></tr>
<tr><td colspan="2">Oxygen</td><td>O</td><td>$H_2O(l)$, $O_2(g)$</td></tr>
<tr><th colspan="6">Mineral Nutrients and their functions</th></tr>
<tr><th colspan="2">Essential crop nutrient</th><th>Symbol</th><th>Primary form</th><th>Deficient Rice crop</th><th>Symptoms</th></tr>
<tr><td rowspan="3">Primary macro nutrients</td><td>Nitrogen
It's a crucial component of chlorophyll. It encourages rapid growth, as well as an increase in plant height and tiller count.</td><td>N</td><td>NH_4^+, NO_3^-</td><td></td><td>Plant has a light green leaf that turns yellow as it gets older, then browns and dies. The plant's growth is slowed, and it will reach maturity early.</td></tr>
<tr><td>Phosphorus
It is crucial in the conversion of energy and the synthesis of proteins.</td><td>P</td><td>HPO_4^{2-}, H_2PO^4</td><td></td><td>The growth of the plant will be slowed and stunted, and the older leaves, particularly on the underside, will be purple in color.</td></tr>
<tr><td>Potassium
It aids in osmotic and ionic control. It confers disease tolerance as well as drought resistance.</td><td>K</td><td>K^+</td><td></td><td>The older leaves' edges will look charred. Plants will be susceptible to disease infestation and will quickly lodge. The production of fruits and seeds would be hampered by poor quality.</td></tr>
<tr><td>Secondary macro nutrients</td><td>Calcium
It is used for cell division and is important for maintaining membrane integrity.</td><td>Ca</td><td>Ca^{2+}</td><td></td><td>The tips of the youngest leaves are white or bleached, rolled, and twisted. Leaf necrosis around the lateral margins and after a long time will turn brown and die.</td></tr>
</table>

Table 3 Continued

Secondary macro nutrients	**Magnesium** It's a crucial component of chlorophyll and it is required by many phosphate enzymes. It's a part of the ribosome's structure.	Mg	Mg^{2+}		Young leaves with interveinal chlorosis and a gradation of pale color next to veins. Plant growth will be sluggish, and disease will be easy to infect some plants.
	Sulfur It plays a role in plant cell energetics, similar to phosphorus. It is important for the synthesis of lipids and amino acids in plants.	S	SO_4^{2-}		As the deficiency worsens, the whole plant turns to light green color, with the older leaves turning from light green to yellow color.
Micronutrients	**Iron** Iron serves as a catalyst in the plant. It is an essential component of many redox reactions in respiration and photosynthesis.	Fe	Fe^{3+}, Fe^{2+}		On the young leaves, interveinal chlorosis will occur, resulting in the bleaching of new growth. When the condition is serious, the entire plant can turn a light green color.
	Manganese It is an O_2 evolving component that is needed for respiration, chlorophyll formation, and nitrate reduction.	Mn	Mn^{2+}		Young leaves have interveinal chlorosis, but the leaves and plants are still green in colour. The plants will be stunted if the infestation is serious.
	Zinc It's an essential part of enzyme systems like dehydrogenases, proteinases, peptidases, etc	Zn	Zn^{2+}		The plants will exhibit interveinal chlorosis in the upper leaves, resulting in the whiting of affected leaves. Tiny, distorted leaves with a rosette shape are possible.
	Copper As a part of metalloenzymes, it regulates certain enzymatic activities as well as catalyzes oxidation reactions.	Cu	Cu^{2+}		The growth of the plant will be sluggish and then stunted with distorted young leaves, which then leads to dying of growing stage.
	Boron It is needed for the production and growth of new cells in the meristem of the plant. It is needed for pollen germination, flower formation, and the absorption of cations.	B	$B(OH)_3$		Young leaves have white and rolled leaf edges. Plant height is reduced. Rising points die, but new tillers arise even when there is a serious deficiency. Plants with a B deficiency are unable to develop panicles.
	Molybdenum It converts nitrate to nitrite. It contains enzymes like Nitrogenase, nitrate reductase, sulphate oxidase, and xanthine hydrogenase	Mo	MoO_4^{2-}		Similar to nitrogen deficiency. Marginal cupping and scorching of leaves.
	Chlorine It is essential for Photosynthesis and the activator of enzymes involved in water splitting.	Cl	Cl^-		Wilting occurs first, accompanied by chlorosis. Excessive lateral root branching. Leaves that have been bronzed Necrosis and chlorosis

In 2017, data mining techniques are used to conduct research in the field of agriculture using soil datasets from various districts in Tamil Nadu. They investigated 12 soil qualities from Ariyalur, Coimbatore, Karur, Salem, Thanjavur, and Trichy, and classified them into type 1, type 2, and type 3 with a hybrid technique that produced a 99.93% accuracy for 3000 data in less classification time [23].

Soil comes in a variety of forms, each with its unique set of features. Because different crops thrive on different types of soils, it's important to understand the qualities and characteristics of each. From the investigations, it is determined which crops will thrive in various soil types [27]. To achieve the greatest soil classification accuracy of 94.95%, SVM is used to input variables such as pH, OC, and soil nutrients. Using classification models such as KNN, naive bayes, and decision tree, the pH, EC, OC, and several macro and micronutrients are utilized to forecast rice crop production. The soil nutrients from Jammu district are analyzed using ML algorithms and archieve a classification accuracy of KNN = 96.43%, Naive Bayes Classifier=97.80%, and Decision Tree Classifier=93.38% [28].

The soil test report data from the Kerala government are collected and used for analysis and prediction in the following analysis [24]. The system employs an Extreme Learning Machine (ELM) with several activation functions, with ELM with a gaussian radial basis activation function being chosen as the best option because it achieves an accuracy of 80%. The authors' system will assist the Kerala government in resolving soil nitrogen deficiency issues. Table 3 lists the important soil nutrients [12][21][30]. These nutrients are critical for a crop to achieve a good yield. Table 4 shows the nutritional levels defined by soil chemists all over India.

The soil nutrients are collected manually from Bangladesh's Soil Research Development Institute (SRDI and then digitized. The technology uses Deep Neural Networks to identify the best crop and forecast 46 yield factors. In comparison to SVM and Random Forest, the deep neural network produces good results [29]. The edaphic parameters (soil qualities) are used to influence plant growth and conduct research using several machine learning models and conclude that ML models give accurate solutions for yield prediction [31].

When compared to other models, SVM gives the best result of 94% when it comes to identifying the proper crop for farming at the right moment. In order to make automatic forecasts, soil fertility indexes are crucial. This will lower the amount of chemical nutrients that must be applied to various cultivated sites. The regression technique with 76 regressors is used for creating a predictive model. When all of the regressors are compared, Extra Trees delivers the best results, with an R^2 of 0.70 [32].

As a result, the survey discusses the key nutrients required for a crop to grow healthy and produce quantitative and qualitative output to benefit society and farmers. Table 5 summarizes the soil nutrients and the algorithms' success in producing a decent yield.

Table 4. Nutrient Levels [23][24]

Level Attribute	Low| Deficient	Medium| Moderate	High | Sufficient
pH	< 6.5 (acidic)	6.5–7.5 (neutral)	> 7.5 (alkaline)
EC	< 1.0 (non-saline)	1.0 – 3.0 (slightly saline)	> 3.0 (saline)
OC	< 0.5	0.5 – 0.75	> 0.75
N	< 280	280 – 450	>450
P	< 11	11 – 22	> 22
K	< 118	118 – 280	> 280
S	< 10	10-15	> 15
Zn	< 1.2	1.2 – 1.8	> 1.8
Fe	< 3.7	3.7 – 8.0	> 8.0
Cu	< 1.2	1.2 – 1.8	> 1.8
Mn	< 2.0	2.0 – 4.0	> 4.0
B	< 0.46	0.46- 1.0	> 1.0

Table 5. Soil Nutrients and their Accuracy measures

Author	Soil Nutrients	Algorithm	Place	Accuracy Measure
E.Manjula et al 2017	pH, EC, OC, macro and micronutrients (12 attributes)	Hybrid approach	Ariyalur, Coimbatore, Karur, Salem, Thanjavur and Trichy	Naive Bayes - 69.9 Decision Tree-90.43 Hybrid approach-99.93
Sk Al Zaminur Rahman et al 2018	Soil nutrients, pH	SVM	Bangladesh	94.95%
Vaneesbeer Singh et al 2017	Macro and micronutrients, pH value	Naïve bayes	Jammu district	KNN-96.43% Naïve bayes-97.80% Decision tree-93.38%
M.S. Suchithra et al 2020	P, K, OC, B, pH	ELM	Kerala	ELM with Gaussian radial bias - 95%
Tanhim Islam et al 2018	Temperature – min and max, average rainfall, humidity, land types, chemical fertilizer, soil types, moisture, texture, consistency, etc	Deep neural network (DNN)	Bangladesh	DNN- 97.7 SVM- 93.3 Random forest- 90.7%
Reashma S R K et al 2017	Soil edaphic factors - Soil moisture, air, temperature, mineral, OC, etc	SVM	Maharashtra	94%
M.S. Sirsat et al 2018	OC, phosphorus pentoxide ($P_2{}^5O$), Fe, Mn and Zn.	Extra trees	Maharashtra	Extra trees (Ensemble model) R^2 - 0.70

4. Challenges and Limitations in Predicting the Crop Yield

The decrease in output is the main issue that the farmers are dealing with. This is due to their lack of understanding of the nutrients that are essential for the crops. Crops will be able to improve their yield if the proper amount of nutrients is provided to them. RNN-LSTM (long short-term memory) model to deduce the data's history using a dataset obtained from indiastat.com. Crop yield prediction considers macro nutrients (N, P, K), pH value, and rainfall, however choosing a dataset and filtering method remains a hurdle for academics [33]. For accurate findings, large datasets (10–15 years of data) should be preprocessed using the optimal selection algorithm. Soil variables are used for statistical analysis and scientific purposes. For predicting crop yield, a similar pace is chosen with similar soil qualities and meteorological circumstances [34].

The second study gap is that data collection is limited to similar land types and adequate soil property choices. As a result, proper soil property selection based on any type of soil should be addressed. As mentioned, varying geographical conditions pose another significant issue for the general construction of prediction models [12]. Farmers face a huge issue in selecting the optimal crop based on factors that influence farming in order to produce accurate production predictions. Crop suggestion systems, according to researchers, are the finest guiding options for farmers [40]. In considering yield prediction of crops in Tamil Nadu with districts related to rice production climatic factor plays a major factor in affecting the yields in consideration with other factors [43]. Predicting the fertility of the soil is also a major challenge faced by the farmers because of the excess use of chemical fertilizers and pesticides [44]. Since Tamil Nadu has a variety of geographical features and farmers are facing more and more dynamic challenges, in digital agriculture, researchers are having problems extracting knowledge from large datasets from a variety of sources [45].

Climate change, particularly rainfall, is the major factor affecting agriculture production. This is one of the most significant issues that farmers face during the entire crop life cycle. The analysis conducted on real-time meteorological data in order to anticipate and improve agricultural productivity shows that the predictions are still challenging because of dynamic changes [46][47].

Understanding the spatiotemporal patterns [49] of a crop is also a barrier for researchers who want to maximize profit with limited resources, and collecting these data remains a substantial challenge. This paper predicts agricultural yield patterns using soil water content, topography, and vegetation state, as well as weather variables [49]. ML techniques are employed to examine topography and climate variables, which are important for land sustainability and productivity. Topography is a critical determinant for quality farming [49][50].

Even though academics are attempting to develop the greatest ideal solutions for farmers, obstacles and restrictions remain. Other issues include the fact that not all farmers will be able to use the programmed design to assist them in smart farming. Because the most important goal to be reached is to assist farmers in generating quality yields, NLP solutions can be provided in such a way that these restrictions are minimized.

5. Results and Discussion

Based on a thorough assessment of agricultural characteristics for yield prediction, ML algorithms provide farmers with optimal decision-making and suggestions, as well as qualitative crop output. The accuracy measures include RMSE, R^2, and MAE to evaluate the success of optimal feature subset selection [38]. The Pearson coefficient (R^2) is the best predictive measure for fertility estimation in soil components [42]. The examination of many ML models yielded three study objectives: (i) categorization of soil fertility, (ii) forecasting the optimum crop for farming, and (iii) yield prediction.

Classification of the Fertility of the Soil

Various studies have used soil datasets such as pH, EC, OC, soil type, macro and micronutrients to predict the fertility of the soil [23][24][27][28][31]. The researchers have utilized several machine learning models such as naive bayes, SVM, ELM, deep neural networks, decision tree, hybrid approach, and random forest, with hybrid, random forest, and ELM being the best models for predicting soil fertility, as shown in Table 1. Table 3 shows the 16 essential soil nutrients used for our study, as well as the pH value, which is a key factor for predicting soil fertility.

Predicting the Suitable Type of Crop

The next stage is to anticipate which crop will thrive in the fertile soil. Various ML algorithms such as RNN, naive bayes, random forest, KNN, and others are used to model soil, water, season, farmer input, support and infrastructure, market price, production rate, and various government policies, soil type, soil fertility, soil pH, maximum temperature, minimum temperature, rainfall, and soil type, soil fertility, soil pH, maximum temperature, minimum temperature, and rainfall. Temperature, pH, humidity, and rainfall are the important parameters required for selecting a good crop, according to the analysis, and the RNN and Random Forest models provide the best option [36][37][39][41].

Yield Prediction

Every farmer's ultimate goal is to predict the crop's output. The studies employed a variety of characteristics to forecast crop output, including climate, state, district, season, pH, water, evapotranspiration, land area, location, soil type, and so on authors [14]-[18] and [26][35]. According to these authors' analysis and conclusions, machine learning techniques like SVM, RNN, deep reinforcement, random forest, C4.5, and regression models perform well on the complicated dataset and provide reliable predictions, as shown in Table 2. Our research findings for agricultural yield prediction show that using effective decision-making ML algorithms like SVM and random forest to choose essential elements such as primary nutrients, pH, organic carbon (OC), rainfall, and temperature can boost the production rate.

The crop chosen for yield prediction is first examined for soil fertility, ensuring that the correct amount of nutrients is applied to the crop and a high-quality yield is produced. A survey of all error metrics concludes that these metrics are the most essential elements in confirming the results [48]. Figure 4 depicts the representation of yield prediction based on the performance measure of various machine learning algorithms, while Figure 5 depicts the representation of soil fertility based on the accuracy of various machine learning algorithms. Several agricultural characteristics are utilized to predict the optimal crop for yield prediction. The essential crop parameters utilized by most writers [33][36][37][40] for predicting the appropriate crop are included in Table 6.

Figure 4 depicts a performance of yield prediction of the Decision tree technique with existing techniques. This clearly shows that the Decision tree technique provided the highest prediction value. With the RSME parameter, the Decision tree approach has a greater prediction value of 0.75%, while the SVM, Naive Bayes, DNN and Random Forest techniques have lesser prediction values of 0.32%, 0.43%, 0.54% and 0.72% respectively. Furthermore, under MAE, the Decision tree approach has a greater prediction value of 0.55%, while the SVM, Naive Bayes, DNN and Random Forest techniques have lesser prediction values of 0.27%, 0.32%, 0.44% and 0.52% respectively. Furthermore, under MSE, the Decision tree approach has a greater prediction value of 0.61%, while the SVM, Naive Bayes, DNN and Random Forest techniques have lesser prediction values of 0.52%, 0.43%, 0.33% and 0.83% respectively.

Under the R^2 factor, the Decision tree approach has a greater prediction value of 0.66%, while the SVM, Naive Bayes, DNN and Random Forest techniques have lesser prediction values of 0.82%, 0.63%, 0.94% and 0.76% respectively.

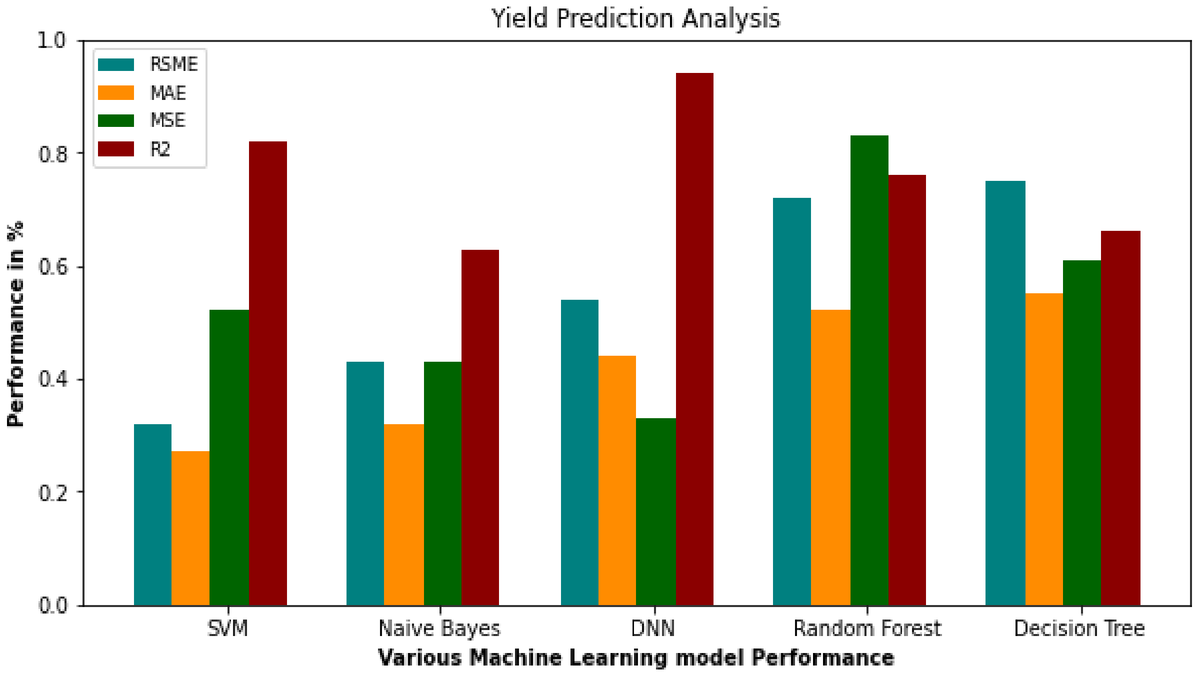

Figure 4. Yield Prediction Analysis

Table 6. Crops suggestion based on crop factors

Soil Type	Rainfall (mm)	N (kg/ha)	P (kg/ha)	K (kg/ha)	pH	Suitable Crop
Black	830	89.5	22.6	4.8	6.5	Cotton
Alluvial	895	81.7	24.3	13.1	6	Paddy
Clay Loamy	500	41.7	14.7	3.8	6.2	Maize
Loamy	600	24.4	39.3	12.9	6.5	Groundnut
Loamy	1100	124.8	44	38.3	7.5	Sugar cane

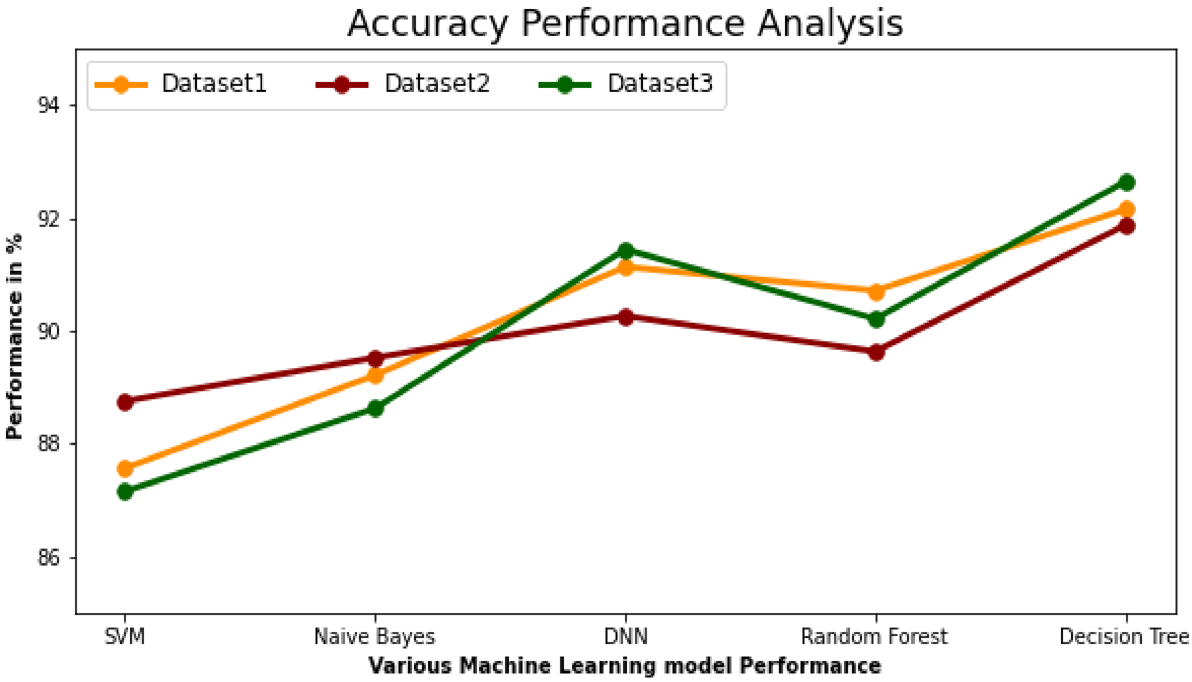

Figure 5. Accuracy Performance Analysis

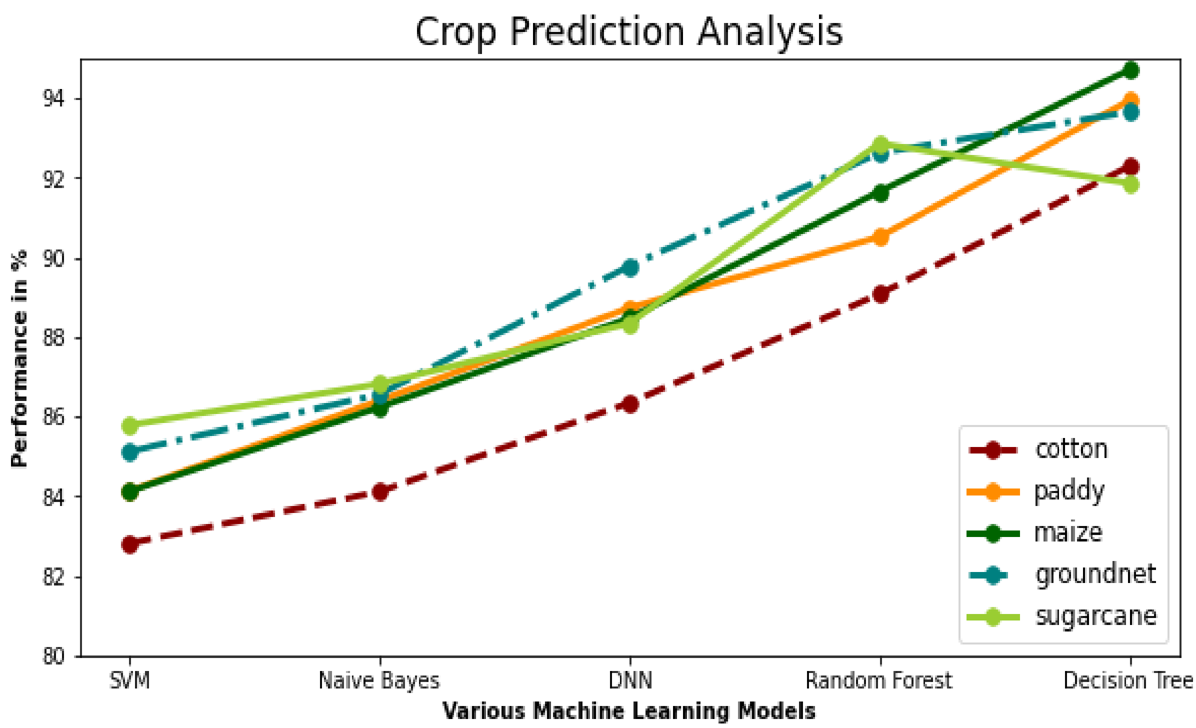

Figure 6. Crop Prediction Analysis

Figure 5 depicts an accuracy comparison of the Decision tree technique to existing techniques. It clearly shows that the Decision tree technique provided the highest accuracy value. For dataset 1, the Decision tree approach has a greater accuracy of 92.15%, while the SVM, Naive Bayes, DNN and Random Forest techniques have lesser accuracy of 87.56%, 89.21%, 91.13%, and 90.71% respectively. Furthermore, under dataset 2, the Decision tree approach has a greater accuracy of 91.87%, while the SVM, Naive Bayes, DNN and Random Forest techniques have lesser accuracy of 88.75%, 89.52%, 90.26%, and 89.63% respectively. Furthermore, under dataset 3, the Decision tree approach has a greater accuracy of 92.64%, while the SVM, Naive Bayes, DNN and Random Forest techniques have lesser accuracy of 87.15%, 88.62%, 91.44% and 90.21% respectively.

Figure 6 depicts a crop prediction analysis of the Decision tree technique to existing techniques. The figure clearly shows that the Decision tree technique provided the highest prediction value. For the cotton crop, the Decision tree approach has a greater prediction value of 92.29%, while the SVM, Naive Bayes, DNN and Random Forest techniques have lesser prediction values of 82.81%, 84.11%, 86.34% and 89.07% respectively. Furthermore, for paddy crops, the Decision tree approach has a greater prediction value of 93.94%, while the SVM, Naive Bayes, DNN and Random Forest techniques have lesser prediction values of 84.13%, 86.4%, 88.73% and 90.51% respectively. Furthermore, for maize crops, the Decision tree approach has a greater prediction value of 94.71%, while the SVM, Naive Bayes, DNN and Random Forest techniques have lesser prediction values of 84.12%, 86.23%, 88.47% and 91.65% respectively. For the groundnut crop, the Decision tree approach has a greater prediction value of 93.65%, while the SVM, Naive Bayes, DNN and Random Forest techniques have lesser prediction values of 85.12%, 86.56%, 89.78% and 92.62% respectively. For the sugarcane crop, the Decision tree approach has a greater prediction value of 91.86%, while the SVM, Naive Bayes, DNN and Random Forest techniques have lesser prediction values of 85.78%, 86.82%, 88.34% and 92.86% respectively.

6. Conclusions

The need for food has increased as a result of the tremendous growth in population. As a result, excessive amounts of chemical fertilizers and pesticides are utilized to increase the quantity, resulting in soil fertility imbalances and barren land. In addition, poor soil and crop management is the primary cause of soil fertility loss. Several classification and regression models, such as decision tree, SVM, DNN, RF, ELM, Kernel Ridge, Lasso, and Linear regression, are used in this article to forecast soil fertility, crop selection, and yield prediction. The performance of these models is evaluated using a variety of standard measures such as RSME, R^2, MAE, and MAPE, all of which reveal that the ML methods used produce low error indices.

In previous studies, the research direction towards choosing the essential soil factors and developing the best decision system is still a challenge among the researchers. This study gives the complete analysis of all the soil nutrients and other environmental factors needed for producing maximum yields.

Also, the major goal of this comprehensive review is to help the researchers to create an intelligent, resilient, and adaptive machine learning approach to categorize and predict soil fertility, as well as to assist the government in managing soil nutrient shortage using a decision system. Also, an AI-assisted, technology-driven farming system will be commonplace, and there will be a strong demand for research into technical interventions that provide optimal results while also assisting farmers in overcoming geographical problems through digital farming.

Conflict of Interest

The authors declare no conflict-of-Interest.

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