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Hydroponic Agriculture with Machine Learning and Deep Learning Methods

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ABSTRACT

In the face of the rapidly increasing world population today, researchers have turned to studies aiming to use existing resources more effectively and efficiently, while also exploring new resources to meet the increasing demands, such as raw materials and nutrients. Hydroponic agriculture has been gaining popularity day by day as one of the alternative methods to fulfill crucial human needs. Its characteristics, including resistance to weather conditions, indoor applicability, and vertical orientation, set hydroponic agriculture apart from traditional methods. The absence of soil in this agricultural approach necessitates more observation and supervision. In this study, the use of machine learning was investigated to overcome the observation and surveillance processes that must be done continuously for the healthy growth of plants. Firstly, we developed a hydroponic prototype to assess this goal. With the developed hydroponic prototype, plant water and wastewater data to be used in the evaluation of the growth and development of plants were obtained by sensors. The data obtained through Arduino was stored in the database and used in the training processes of machine learning algorithms. Our experimental study, which utilized five machine learning and deep learning methods, demonstrated a significant increase in hydroponic agricultural efficiency. Notably, deep learning outperformed other methods with a 99.7% success rate. In conclusion, our study shows that machine learning can be used effectively in hydroponic agriculture by providing observation and surveillance of plants.

Makine Öğrenmesi ve Derin Öğrenme Yöntemleri ile Hidroponik Tarım

ÖZ

Bugün dünyanın hızla artan nüfusu karşısında, araştırmacılar var olan kaynakları daha etkili ve verimli bir şekilde kullanmayı amaçlayan çalışmalara dönmüşler, aynı zamanda hammaddeler ve besin maddeleri gibi artan talepleri karşılamak için yeni kaynakları keşfetmişlerdir. Hidroponik tarım, kritik insan ihtiyaçlarını karşılamak için kullanılabilecek alternatif yöntemlerden biri olarak gün geçtikçe popülerlik kazanmaktadır. Hidroponik tarımın, hava koşullarından etkilenmemesi, kapalı alanlarda uygulanabilmesi ve dikey yönlendirilebilmesi gibi özellikleri, onu geleneksel yöntemlerden ayıran özelliklerdir. Bu tarım yönteminde toprak eksikliği, daha fazla gözlem ve denetim gerektirir. Bu çalışmada bitkilerin sağlıklı büyümesi için sürekli yapılması gereken gözlem ve gözetim işlemlerinin üstesinden gelmek için makine öğrenmesinin kullanımı araştırılmıştır. Bu hedefi değerlendirmek için ilk olarak hidroponik bir prototip geliştirilmiştir. Geliştirilen hidroponik prototip ile bitkilerin büyüme ve gelişmesinin değerlendirilmesinde kullanılacak bitki suyu ve atıksu verileri sensörler aracılığıyla elde edilmiştir. Arduino üzerinden elde edilen veriler veri tabanında saklanarak makine öğrenmesi algoritmalarının eğitim süreçlerinde kullanılmıştır. Beş makine öğrenimi ve derin öğrenme yöntemlerini kullanan deneysel çalışmalarımız, hidroponik tarım verimliliğinde önemli bir artış olduğunu ortaya koymuştur. Özellikle derin öğrenme yöneteni %99,7 başarı oranıyla diğer yöntemlerden daha iyi performans göstermiştir. Sonuç olarak çalışmamız, bitkilerin gözlem ve gözetiminide sağlayarak makine öğreniminin topraksız tarımda etkin bir şekilde kullanılabileceğini göstermektedir.

Anahtar Kelimeler: Akıllı Tarım, Makine Öğrenmesi, Derin Öğrenme

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1. Introduction

The rate at which resources are used up or worn down is much higher than the rate at which they are replaced around the world [1]. As food sources like soil and water get less, the need for nutrients keeps going up. This makes it harder to find enough food for everyone. This stress causes the need for researchers to conduct urgent studies with the aim of finding alternative, sustainable, and reliable methods for existing resources.

In the calculations made by the researchers on the population growth rates in the coming years, it is estimated that the global population will increase to about 10 billion by 2050. With this estimate, it has been found that a 50% increase in nutrients around the world is needed to meet the growing population's nutritional needs. This rate of increase in the need for food source production was compared with the decrease in the rural labor force, which decreased due to increasing urbanization. The researchers also predicted that 66% of the world's total population will live in cities by 2050. People have noticed that the world's food production needs to go up by 70% in the next few years compared to what it is now because the population is expected to grow and the number of people working in rural areas is going down.

For this needed increase in food production, researchers have looked into ways to make food that is more efficient and lasts longer than traditional farming methods. One of these methods, hydroponic farming, is becoming more popular around the world because it makes better use of water and fertilizer and gives farmers better control over the weather and other bad things [2].

With the advantage of hydroponic agriculture over climatic conditions, it has become possible to grow tropical climate plants in places that would not be suitable under natural conditions. [3], in his research aim is tropical hydroponic cultivation which needs to control the humidity, temperature, water level, pH and EC factors suitable for a tropical climate. In order to grow qualified hydroponic plants, the nutrient solution must constantly pass through the subchannels, and the pH and EC factors in the solution must control the hydroponic plant varieties as the plant ages, as well as the food safety adequacy. Some researchers, such as [4], [5], [6], [7] have investigated using microcontrollers for system controls, while some researchers, such as [8], have used some sensors and controls to control the nutrient solution. And others, such as [9], used machine learning methods for disease detection of hydroponic plants.

The implementation of sophisticated technologies, including the Internet of Things (IoT), machine learning, and artificial intelligence (AI), is utilized in smart farming to enhance agricultural processes and efficiency [10, 11]. The methodology employed in this study involves the utilization of sensors and Internet of Things (IoT) devices for the purpose of gathering real-time data pertaining to soil moisture, temperature, and crop health. This data-driven approach facilitates informed decision-making processes [11].

One significant advantage is in the realm of operational efficiency. The utilization of monitoring sensor data in agricultural practices enables farmers to optimize the allocation of resources such as water and fertilizer, resulting in enhanced crop yields and minimized resource wastage [11]. According to [12], the implementation of smart farming techniques has been found to effectively decrease the utilization of pesticides, hence mitigating the potential environmental consequences associated with their usage.

Another benefit that may be derived from this is the optimization of budget allocation. According to [11], the use of automation and data analysis in large-scale farms has been found to result in reduced labor costs and improved equipment efficacy. The use of smart farming techniques has been found to enhance energy efficiency, namely in the areas of irrigation and greenhouse management, hence contributing to the promotion of sustainability [10,12].

The practice of forecasting has significant value as it enables professionals to make predictions regarding agricultural yields, market demand, and weather patterns [10]. This facilitates the process of strategy planning and the establishment of market positioning.

According to [12], the utilization of Internet of Things (IoT) and artificial intelligence (AI) enables farmers to effectively monitor and manage irrigation and greenhouse conditions, hence enhancing operational efficiency.

Notwithstanding the advantages outlined above, smart farming encounters many problems. According to [11], there exist notable obstacles in the form of implementation costs, knowledge acquisition, and data protection issues.

An experimental hydroponic farming system has been installed for the study. Arduino based systems have been used to create tasks such as monitoring the system and collecting system data. Machine learning and deep learning techniques are used to process the collected data. The goal of this study is to look at the problem of attention and supervision that can be fixed with machines. In addition to the deep learning technique, the SVM, kNN, naive bayes, decision tree, and logistic regression techniques were also used in this study. As a result of the research, machine learning techniques for the system have reached a high level of performance. However, deep learning methods demonstrated the highest performance.

Table 1. Comparison of Sensors Used in Various Studies

Research	Observation	Control	pH	EC	TDS	Water Level	Temperature and Humidity	Light	Water Temperature	light intensity
[13]	X	X	X			X	X			
[14]	X	X					X	X		
[15]	X	X	X	X						
[16]	X	X	X	X						
[17]	X	X	X	X			X			
[18]	X	X	X	X						X

The remainder of the paper consists of the following: Section II provides background information on machine learning techniques, deep neural networks, and IoT-based hydroponic system. Section III contains the results and analysis. Section IV concludes the paper and discusses the future direction of the topic. Section V concludes the feature work.

2. Methods

2.1. Prototype Setup

In this study, an experimental system has been established to support our thesis. Arduino sensors were used in the experimental system. The reason for choosing Arduino sensors is that it's an open and comprehensive network of smart objects with the capacity to automatically organize, share information, data, and resources, react, and take action in the face of situations and changes in the environment. [2]. Arduino is first and foremost an open-source computer hardware and software company. Additionally, it is widely utilized and accessible. It is inexpensive and simple to access.

The techniques shown in Figure 1 is the Arduino design. Which was made as a prototype, were used to get the data set that was used in this study. In hydroponic agriculture, the measurement of production in large areas is carried out once or twice a day. In this article, however, data was collected every 4 hours to track how plants grew, taking into account that the system was made up of 12 tomato seedlings.

The system used has a nutrient solution arrangement that works with artificial light and a drip system, as shown in Figure 2. The value measurement in the nutrient solution was collected with the help of Arduino sensors. The collected values are pH, EC, ppm, and water temperature values, which are valuable in terms of following the development of the plant.

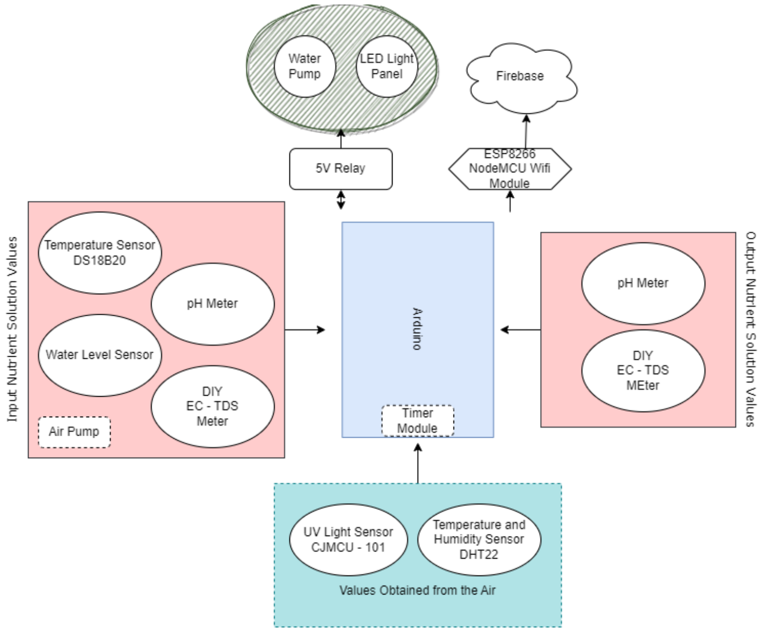

Figure 1. Prototype Arduino installation diagram and demonstration

In the same way, Arduino sensors were used to measure the air temperature, humidity, and the amount of artificial light. In addition to collecting all this data, Arduino has also decided on the irrigation and light status with the help of the timer module. At the same time, the water level in the nutrient solution was measured with a water level sensor.

The operation of the system utilized an Arduino Uno board. After measuring the nutrient solution for values, it was sent to the system, and the aim was to obtain information about the system by measuring the wastewater after plant usage. In the water solution input basin of the system, a water temperature sensor (DS18B20), a pH module for measuring the water's pH level, and a water level sensor were used in conjunction with a homemade EC-TDS meter to measure the presence of water in the reservoir.

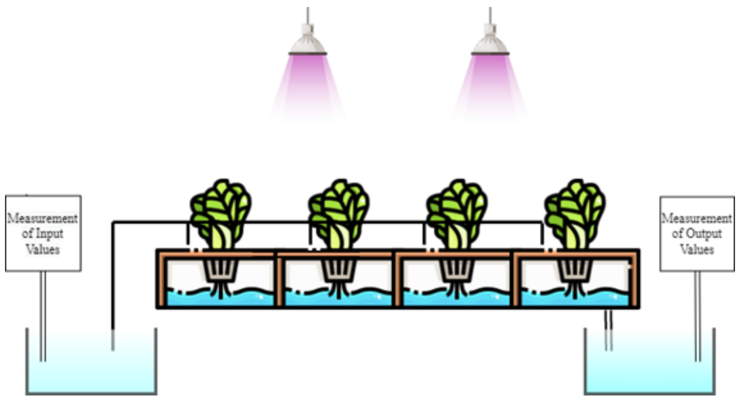

Figure 2. Hydroponic agriculture prototype scheme

After the system used the nutrient solution, pH, EC, and TDS meter modules were employed to gather information about the wastewater produced by the system. Furthermore, the water and light provided to the system were controlled by a 5V relay connected to an Arduino Uno through a timer. The weather conditions at the location of the experiment were also monitored. The humidity and temperature sensor (DHT22) was used for continuous monitoring of humidity and temperature in the air. Additionally, the light intensity, which is another factor affecting plant growth, was monitored using an analog light intensity sensor (CJMCU-101).

To enable the transfer of all these collected values to the Firebase database system, a NodeMCU ESP8266 was used as the Wi-Fi module. When transferring the values to the database, input values such as pH, EC, and TDS, as well as output values, were labeled as "In" and "Out," respectively. To carry out all of these processes, the Arduino Uno was programmed using the Arduino IDE with the C programming language.

2.2. Dataset

Out of all the values that were measured, pH and EC need to be put into groups so that the state of the system can be better understood. This classification for pH is used when the system is basic, acidic, or natural. Classification for EC, the nutrient solution requires water, the nutrient solution requires additional nutrients, and the solution is balanced.

Table 2. pH and EC classifications

pHIn-pHOut=pH	-0.5<pH<0.5	0	Natural
	pH< - 0.5	1	Basic
	pH > 0.5	2	Acidic
ECIn-ECOut=EC	-1 < EC <1	0	Balance
	EC < -1	1	Add Nutrient To Solution
	EC > 1	2	Add Water To Solution

To comprehend how the plant utilizes the nutrient solution, it is essential to examine the difference between the waste nutrient solution obtained after the plant's use and the nutrient solution provided to the plant. This allows for insights into how the plant utilizes nutrients in the given solutions. In many studies, various pH and EC (Electrical Conductivity) values are suggested for tomato cultivation. Generally accepted pH values typically fall within the range of 5.0 to 7.0, while the EC value is commonly recommended to be between 0.5 and 1.8. These values can vary depending on the plant species. For this system, equilibrium points were chosen not only as zero but also as positions closest to zero, considering the system's margin of error.

For the system, the light and irrigation status, which are the main factors in the development of the plant, were transferred to the database with a value called "Status". How this value is classified and the number of examples in this classification are explained in the example of Table 2 below.

Table 3. System status and the number of data corresponding to the states

Irrigation Status	**Light Status**	**Status**
Close	Close	0
Close	Open	1
Open	Close	2
Open	Open	3

2.3. Algorithms

Machine learning is a field of computer algorithms that are currently being used to mimic human intelligence by learning from their surroundings. In numerous areas of research, including pattern recognition, computer vision, spacecraft engineering, finance, entertainment, computational biology, and biomedical applications, machine learning techniques have been successfully implemented [19]. In this study, SVM, kNN, logistic regression, decision tree, and naive bayes were used to determine the system state and nutrient solution values. All algorithms were written using Python language with Keras, scikit learn libraries via Google collab.

2.3.1. Support Vector Machine (SVM)

Support Vector Machines (SVM) have seen an increasing demand due to their accuracy rate in classification, robustness, and independence from the input data type. The SVM method, which was initially designed for use in binary classification, was created by Vapnik [20] in order to solve the quadratic optimization problem [21]. As an application of statistical learning theory, the SVM was created to solve classification problems with large margins. It creates a separating hyperplane and a maximum margin in the absence of training data by selecting a subset of SV⊂X known as support vectors [22].

2.3.2. Naive Bayes

The basic idea behind the naive Bayesian method is that it is a classification method based on probability that assumes the dependent variable is not important. It is also a Bayesian conditional model [23] based on Bayes' theorem. The naive Bayesian method is a classification technique. It is founded on the Bayes theorem and the notion that characteristic conditions are true by themselves [24]. The naive Bayesian algorithm has stable classification accuracy and a solid mathematical basis. In this method, each attribute is separate from the others and doesn't affect the others. This makes it easier to determine the likelihood of something [25].

2.3.3. Decision Tree

A decision tree is a tree-based method where each node, starting with the root, represents an attribute and a set of data classifications until the last node, the leaf, gives a boolean result. In real-life practice, each path in the decision tree is a decision rule that can be easily translated into human languages or programming languages. When all paths (rules) are examined beginning at the root. The entire tree resembles a conjunctional expression. Disjunctions are used to make classification boolean decisions that take each attribute test into account [26, 27].

2.3.4. K-Nearest Neighbor

K-Nearest Neighbors is one of the most popular and widely used machine-learning algorithms. Its applications include image or data retrieval, data mining, medical and satellite imaging, computer vision, speech recognition, text categorization, big data analysis, data compression, computational genomics, and predictive analysis [28, 29]. Calculate their distance to all of the sample data in a training set with known classes. The class that occurs the most frequently among the k training samples that are closest to the classified data is then decoded [30].

2.3.5. Logistic Regression

The logistic regression analysis model is a generalized linear regression analysis model that is widely used in economic forecasting, automated disease diagnosis, data mining, and other fields. It is a method of regression analysis that is frequently used as a correlation analysis. The appropriate regression model is chosen in order to determine a more precise quantitative correlation between its parameters. The variables that influence logistic regression can be classified into two or more groups [31].

2.3.6. Deep Neural Network (DNN)

Deep learning is a machine learning technique that has existed for the past decade. It is distinguished by its refined approach. Learning through deep neural networks enables computational models to acquire multiple levels of abstraction in their data representations. These models consist of several processing layers. These techniques have significantly advanced the state of the art in numerous fields, including drug discovery and genomics, speech recognition, the recognition of visual objects and objects in general, as well as genomics. In the past, it was thought that neural networks could be effective with only one or two layers and a small amount of data. Today, neural networks are utilized with a great deal more learning capacity [32]. Deep learning identifies complex structures in large data sets by using the backpropagation algorithm to indicate how the internal parameters of a machine used to compute the representation in each layer from the representation in the previous layer should be modified. Deep convolutional neural networks have advanced the processing of images, video, speech, and audio, whereas recurrent neural networks have shed light on sequential data such as text and speech [33].

In this study, seven layers were utilized in the neural network architecture. Sigmoid activation was employed in all layers up to the final one. Softmax activation was used in the last layer. Adamax was the optimization algorithm of choice. Categorical cross-entropy was employed as the loss function, typically used in multi-class classification tasks. These are used in tasks where an instance can belong to one of several possible categories, and the model needs to make a decision among them.

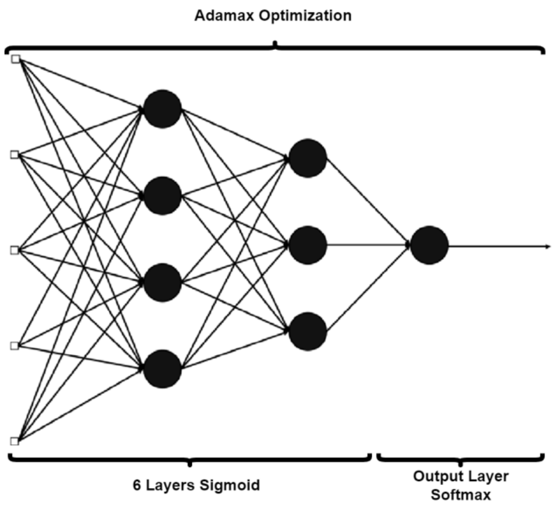

Figure 3. Deep learning model

2.3.7. Convolutional Neural Network (CNN)

CNNs are particularly effective in image recognition and classification tasks. They are designed to automatically learn and extract features from images through convolutional layers, pooling layers, and fully connected layers. CNNs have been widely used in applications such as object detection, facial recognition, and image segmentation [34].

The neural network in this study is seven-layered. 'ReLU' activated convolutional layer non-linearity and feature extraction. Max-pooling with 2 pools used less space. A one-dimensional vector was constructed from multidimensional data. Two deep layers with 128 neurons increased the model's complex data pattern interpretation. The last layer, essential for multi-class classification, employs the 'Softmax' activation function to convert the network's output into probability distributions for the four classes. The 'Adam' optimizer with 'categorical cross-entropy' loss function improved the model's parameters for tasks where examples may belong to many categories and the model must make intelligent judgments. The dataset-learning model ran 10 64-batch data processing epochs.

2.3.8. Recurrent Neural Network (RNN)

RNNs, on the other hand, are designed to process sequential data, such as text or time series data. They have a recurrent structure that allows them to retain information from previous steps and use it to make predictions or generate output. RNNs are commonly used in tasks such as language modeling, machine translation, and speech recognition [34].

This study created a classification neural network model using the Simple Recurrent Neural Network (SimpleRNN) architecture. A 64-neuron SimpleRNN layer uses the 'ReLU' activation function to introduce non-linearity to the network in the model's three levels. Two thick layers with 128 'ReLU-activated neurons' follow this layer. Multi-class classification requires the last layer to use the 'Softmax' activation function to generate probability distributions over the four classes to help the model classify input examples. For tasks containing examples belonging to several categories, the 'Adam' optimizer with a 'categorical cross-entropy' loss function was used to optimize model parameters. The model was trained for 10 epochs with 64-batch data to iteratively learn from the dataset.

2.3.9. Long Short-Term Memory (LSTM)

LSTMs are a type of RNN that address the vanishing gradient problem, which can occur when training traditional RNNs on long sequences. LSTMs have a more complex architecture that includes memory cells and gates, allowing them to capture long-term dependencies in the data. LSTMs have been successful in tasks such as sentiment analysis, speech recognition, and handwriting recognition [34].

This study used LSTM architecture to build a neural network model that captures sequential data interactions. The model contains three layers, starting with a 64-memory LSTM. This layer uses the 'ReLU' activation function to encode temporal information in the data to make the model non-linear. The LSTM layer is followed by two thick layers with 128 neurons and 'ReLU' activation functions. The final layer's 'Softmax' activation function turns model output into probability distributions across the four target classes, making it essential to multi-class classification. The 'Adam' optimizer and 'categorical cross-entropy' loss function optimized and trained the model for multi-category problems. The model learns and improves during ten 64-batch data processing epochs.

3. Results and Discussion

The primary objective of this article is to address the fundamental issue that hydroponic agriculture is significantly more susceptible to environmental variables than soil-based agriculture. For this purpose, the performance criteria used when applying machine learning methods are given in the Table 3.

Table 4. Performance Metrics

Performance Metric	Equation
Accuracy	(TN + TP) / Total Test Data
Precision	TP / (FP + TP)
Recall	TP / (FN + TP)
F1-Score	2 * ((Precision * Recall) / (Precision + Recall))

In the first step, it was determined whether the machine learning methods had learned the fundamental lighting and irrigation techniques that made the prototype functional. Figure 3 displays the results obtained by the "Status" value using various machine learning techniques.

According to the results, SVM, Guessean Naive Bayes, and Decision Tree are the most appropriate techniques for predicting the system state. In all types of evaluations, it has achieved a success rate of greater than %95 using these techniques. As a result of these findings, it has been determined that machine learning techniques can be relied upon for system control.

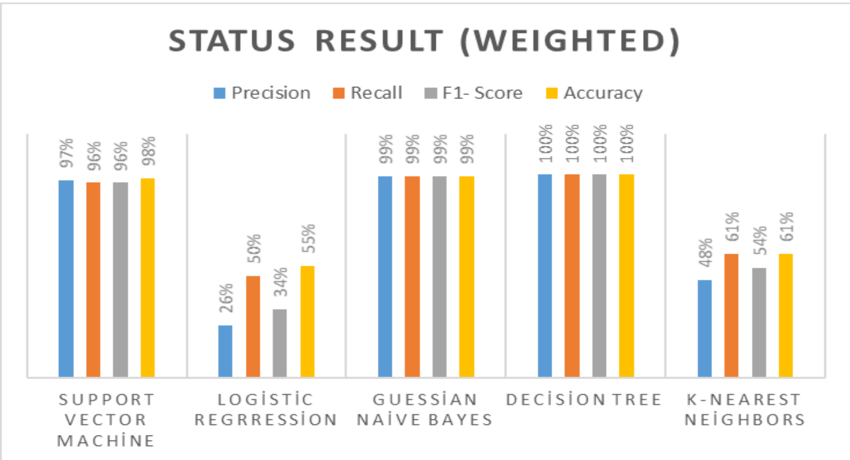

Figure 4. Machine learning results for the status value

In hydroponic systems, the values of EC and pH must be constantly monitored. Changes in these values indicate whether or not the system as a whole is healthy. This is the area in which this person's expertise in agriculture management is most needed. Therefore, can machine learning methods be used to automatically control these areas? Figure 4 depicts the outcomes of evaluating various machine learning algorithms on their ability to predict the answer values to this question.

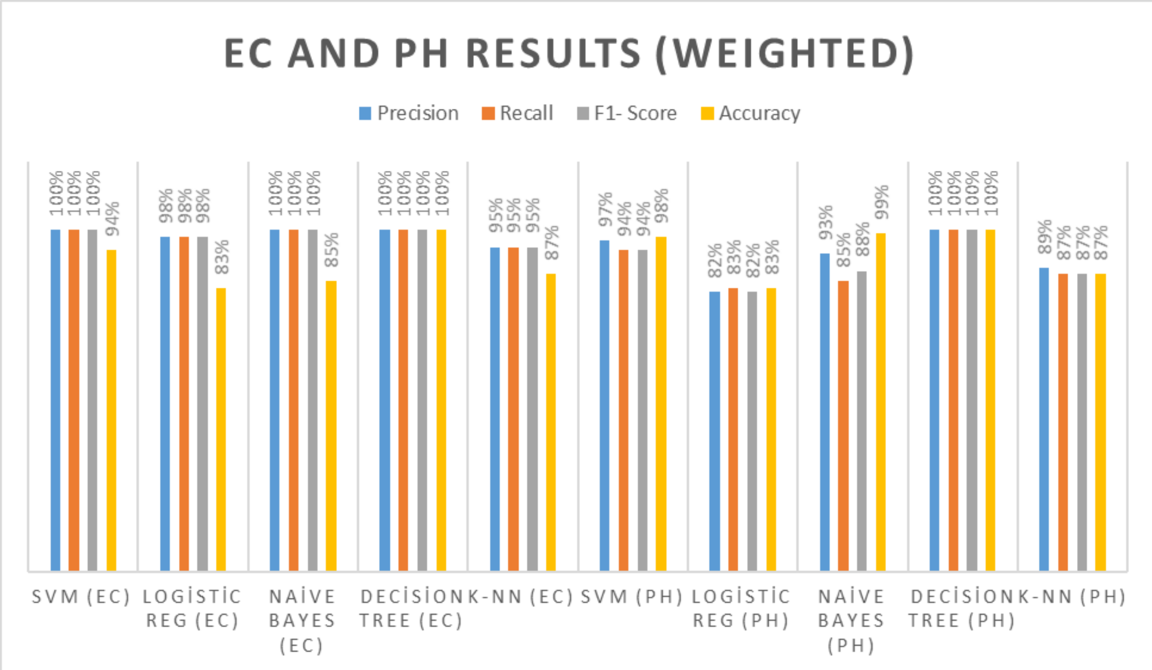

Figure 5. Results of machine learning for the EC and pH value

As seen in the table above, the results of machine learning now exceed 80%. Compared to this situation, when machine learning methods were employed, the estimated EC and pH values produced superior results compared to all other methods.

In addition to machine learning, deep learning techniques were used to determine the operation of the system. Since these methods work primarily with large data sets, the data were augmented using the SMOTE data analysis method, and an equal number of data samples were collected for each classification. The results are shown in Table 3.

Table 5. Before and after smote data analysis

Class	Before smote	After smote
0	91	177
1	177	177
2	24	177
3	41	177
Sum	333	708

After the SMOTE data analysis process, deep learning was applied to the augmented data. Deep learning has a structure consisting of layers. Seven layers were used in this study. Sigmoid activation was used until the last layer. The sigmoid activation function introduces additional adaptive parameters to control the maximum value, steepness, and scaled horizontal displacement of the sigmoidal curve [35]. In the last layer, Softmax is used. The Softmax function is often used in the final layer of DNN-based classifiers. Softmax function contains massive exponential and division operations, resulting in high resource usage when implemented as hardware [36]. Adamax was used for optimization, an algorithm for first-order gradient-based optimization of stochastic objective functions, based on adaptive estimates of lower-order moments [37]. Categorical cross entropy is a loss function used in multi-class classification tasks. These are tasks in which a sample can belong to only one of many possible categories, and the model must decide one of them. Formally, it is decisively designed to measure the difference between two probability distributions.

Table 6. DNN results

Modele	Precision	Recall	F1- Score	Accuracy
DNN	0.997	0.997	0.997	99,7%
CNN	0.256	0.5	0.338	50%
RNN	0.018	0.095	0.030	9.5%
LSTM	0.405	0.511	0.428	51.19%

This study aimed to evaluate the efficacy of different machine learning models, including CNN, RNN, LSTM, and DNN, in the context of a four-class classification job. The summary findings for each model are presented below.

The convolutional neural network (CNN) model demonstrated a 50% accuracy rate, suggesting a performance superior to that of random guessing in the context of a four-class issue. Nevertheless, there is scope for enhancement, namely in terms of accuracy and the F1-Score, indicating a higher occurrence of false positive predictions and overlooked real positives.

The recurrent neural network (RNN) model demonstrated suboptimal performance, achieving just a 9.5% accuracy rate. Significant deficiencies in accuracy and recall metrics suggest difficulties in accurately categorizing positive situations and identifying true positives. The poor F1-Score serves as evidence of the general insufficiency of this model.

The LSTM model exhibited superior performance compared to the other models, with an accuracy rate of 51.2%. The results exhibited superior precision and recall in comparison, indicating enhanced accuracy in predicting positive class instances and detecting genuine positives. A higher F1-Score is indicative of improved overall performance.

The deep neural network (DNN) model demonstrated outstanding performance, with a precision, recall, F1-Score, and accuracy of 99.7%. The aforementioned model demonstrated a high level of accuracy in correctly classifying positive cases and effectively identifying real positives, hence establishing itself as the most successful model among those that were assessed.

In summary, it can be concluded that the LSTM model had superior performance compared to the CNN and RNN models. However, it is noteworthy that the DNN model shown much better performance than all other models. Nevertheless, there is still potential for further enhancement in all models. Subsequent research endeavors should take into account many elements such as the size of the dataset, the selection of features, and the optimization of model hyperparameters in order to improve the outcomes of classification.

When all of this is taken into consideration, it has been found that the performance rate achieved by using the data set with the DNN model that was created is higher than that achieved by using any other machine learning models.

4. Conclusions

The concern over meeting the nutritional needs of the world's growing population has focused researchers on new methods. Hydroponic agriculture, which is one of these methods, has come forward with advantages such as being independent of climatic conditions, having a lot of production capacity in a small area, and not using soil. With all these advantages, the lack of soil also brings with it the problem that plants are more sensitive to stimuli. In this research, machine learning methods such as SVM, kNN, decision trees, naive bayes, and logistic regression are used to solve the problem, as well as deep learning methods.

The primary objective of this research is to explore whether qualified individuals necessary for hydroponic agricultural techniques may be replaced by machines. This article's findings show that machine learning algorithms potentially replace humans in hydroponic agriculture with an accuracy of above 80%. Furthermore, deep neural networks(DNN) have such a 99% successful rate in replacing qualified personnel. The results of the research, based on data obtained from a prototype system, indicate that machines can predict the system with higher accuracy, especially in forecasting EC and pH values. In addition, the developed machine learning based prototype be used desicion support system for hydroponic farmers.

5. Feature Work

The subsequent research may investigate the use of hybrid algorithmic approaches. Another approach is to use different DNN layers and optimizations. On the other hand, the system's dependability can be compared to that of a system that is well-prepared and well-grounded.

Conflict of Interest Statement

The authors declare that there is no conflict of interest

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