E-ISSN: 3107-5843
International Journal of Advanced Engineering and Management System
Volume 01, Issue 01, April-June 2025, pp. 51 - 64

Sustainable Crop Yield Forecasting Using Advanced Machine Learning Techniques Based on Comprehensive Analysis of Soil Health Parameters and Environmental Factors

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Abstract:

Crop failure due to drought periods may affect crop yield due to climatic variation, and natural disasters may affect soil health in the agricultural environment. Factors that impact soil health, such as filtering the natural water quality level. Forecasting tools are used to identify future trends in the soil robotic sensor to improve the accuracy of crop yield. In this paper, we study the real-time data monitoring for accurate prediction to help traders to better decisions. The best-fit Proximal Policy Optimization (PPO)model is chosen by finding a specific location to crop the yield in the environment. The output of such an interpretable model could improve valuable forecasting for plant growth. This approach can achieve 96% accuracy in solving a complex problem. This computational result is cost-effective and intelligent farming for predicting yield and resource allocation in farming. Precision agriculture for early detection, for planning a model for long-term food security, and for real-time agricultural decision making. To forecast crop yield monitoring of health care parameters for environmental factors, Remote sensing, and robotic soil sensors for real-time data. Crop specification for land location to reduce the impact of soil climate change variability. Agriculture is a critical sector for rising food demand and soil health parameters such as pH, moisture content, and nutrient concentration. The study of PPO stands for Proximal Policy Optimization, a powerful tool for smart agricultural farming.

Key words: Q-learning, Deep Q-Networks, Proximal Policy Optimization (PPO), Machine learning models, Crop yield prediction, Soil health parameter, Smart agriculture, Remote sensing, GIS and GPS, Real time monitoring, Soil quality testing, Climate forecasting, Robotic sensing.

1. Introduction

Crop is an essential need in the agricultural environment sector to feed food, and humans depend on growing crops. Forest land is not suitable for planting and growing crops because climatic changes can affect the environment, soil quality, and sunlight are important for crop yield [1]. In traditional methods using farmers, time-consuming, long-term scheduled processes, tool requirements, resource availability, and impact on the planning process are also complex in manual farming [2]. Global population for food demand crop is not based on populational growth, maintaining soil, increasing the rate of food storage, and Continued growth of population [1]. Real-time monitoring of crop yield is a secure form a disease detection of risk, reduces manpower effects, and reduces time [3].

Soil testing is an important and necessary step in the agricultural department to test the water scarcity level and soil health quality, to secure a natural underground water level [4]. Avoid fertilizer for growing plants earthworms present in the soil are affected due to pesticides [5]. Aware of the environmental impact, waste dumping on the river affects soil and crop yield in the agricultural sector, and avoid dumping plastic waste in the soil [6]. Airline craft like drones contain cameras like eyes to watch the outer environment and observe and capture an image [7]. Soil is a home for earthworms to protect soil living organisms to live freely in the natural, healthy soil and plant a healthy crop, and grow plants in the soil [8].

Preparing soil to add manure, feed essential nutrients to the soil, and separate unwanted plants to harvest, supplying water to the soil for healthy plants [9]. To maintain a PH level in a soil to find the accuracy of planting crops, to protect the soil, and reduce erosion [10]. By using Precision agriculture for farmers to make better decisions making and low cost due to the use of GIS (Geographic Information System) and GPS (Global Positioning System) software for mapping the location [11]. Agriculture is an important one in Indian economic policy as a backbone of the population, according to the factors of crop selection and planning [12]. Climatic conditions also cause an agricultural land to determine which crops to yield in the specified area based on humidity, rainfall, sunlight, wind, and temperature; these are the main elements focused on the agricultural field [13].

To select a suitable crop type for suitable land [14]. Ensuring the rice is an available demand and occupies more area in a land with low cost and long duration [15]. Identify a soil temperature, what type of soil, and how a soil is best matched for crop yield [16]. Harvesting is an important stage in the cultivation of yield sustains to people and the economy [17]. Forecasting is a method to look ahead from the preprocessing stage for better results [18]. Using modern tools to predict an accurate result for yielding crops in an agricultural land [19]. Early detection is a method to warn earlier stage of crop growth to get information [20]. The quality and quantity of the crops are determined in crop analysis [21].

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2. Computational framework

Soil health parameters for crop yield prediction using an algorithm called Q-learning, Deep Q-Networks, and Proximal Policy Optimization (PPO) are the source parameters collected in **Table 7** represent soil features like pH, Organic matter, potassium(K), Phosphorus(P), and nitrogen (N). Soil moisture level produced an electric conductivity based on the climatic variations like temperature and rainfall. **Figure 1** below represents a plot of soil health parameters for cleaning data using preprocessing steps. Techniques are implemented using feature selection, model development, and used data to train and test as discussed in the following.

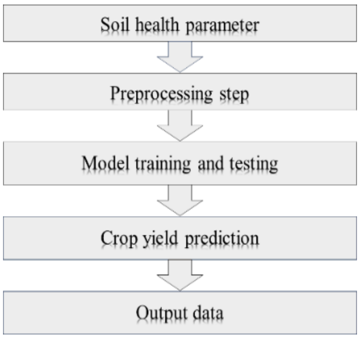

Figure 1. Yield prediction model flow diagram

2.1 Data Gathering

Soil data is collected from pH level in the soil, Moisture content in the soil, Nitrogen for crop growth, Phosphorus for plant health, and Potassium level in the soil to be tested in the labs. **Table 1,6** represents Soil health data like pH level, Nitrogen, Phosphorus (P), Potassium (K), Moisture content, and Organic matter. Environmental data like soil temperature, Humidity, and Rainfall are represented in **Table 8 and Figure 10**. Crop yield data, like historical crop yield used as a target output prediction. Crop yield data for prediction in locational analysis using Geographical Information System (GIS). Soil testing for research in agricultural institutes. Source data is collected from the Kaggle dataset and the UCI machine learning dataset. Using remote sensing tools like satellites and drones for monitoring the yield in real time.

2.2 Data Preprocessing

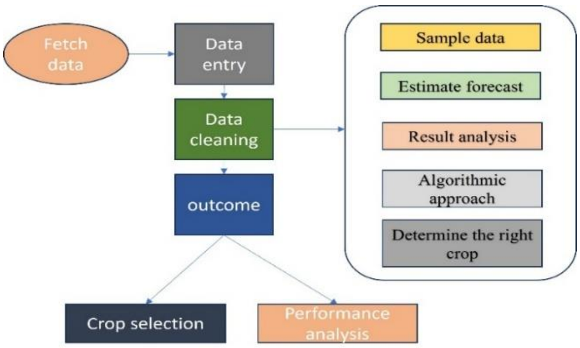

Figure 2. Data preprocessing stages

Preprocessing is a method to clean and remove unwanted noise in the soil and to make the data clean and secure. Make a data stability and standard-rich quality for normalization. **Figure 8** represents a separate soil based on type and also separates a crop based on type. Data are split into training and testing. Training data contains 80% and testing data contains 20% of the dataset. The above **Figure 2** represents the data to remove duplicate values and make the data identical for missing values. Training and testing a data set with a ratio of 80:20 data model was normalized. Raw data is removed in the preprocessing step to make the data more structured for real-time entry. To ensure a data high quality of health parameters to yield crops for accurate prediction.

2.3 Feature Selection

Soil parameter focuses on soil health to predict a high accuracy. Soil temperature is a major focus on crop growth. Key parameters for soil health include physical and chemical factors. **Table 2** represents the main objective is to making a model for high performance. Machine learning approach for Accurate crop yield prediction from soil health parameters to select the best crop for yield. To improve performance and model accuracy prediction for overfitting. Low-cost computation model for better interpretability of variables to predict output. Water availability for crop yield and check the quantity level for flowering plant growth and development. Early growth and water absorption capacity in the soil are monitored for crop yield, for strong growth requirements.

2.4 Model Selection and Training

By choosing a model to train the data and test the data to learn a model, and by choosing an overfitting method for preparing and selecting alternatives. Training a model to identify model performance, selecting a perfect algorithm for model evaluation. The Configuration model for the training process selected a model to predict the parameter. Q-learning, Deep Q-networks (DQN), and proximal policy optimization are the three alternative categorized model selection to implement plant growth.

2.4.1 Q-Learning

The robotic agent interacts with a real-world environment to build a good relationship and learns to solve a real-world problem. The robotic agent works in the environment. The robotic tool acts as a positive or negative to the environment in action. From each result, the robotic agent takes the best result Q-learning formulas are used to update the result.

$$Q(s,a) = Q(s,a)\alpha[r_t + \gamma maxQ(s',a') - Q(s,a)] \quad (1)$$

$$A^t = T_r - W(t,s) \quad (2)$$

Q (s, a) represents the present value of the current score for taking action a in state b. α represents a learning rate from past to future values. R represents an immediate score that occurs after an action. Γ represents a factor of discount for future action. q (s′. a′) highest score expected for future state. A represents the current state action, and b represents a present action. s′ represents a future state actionand a′ represents a next action. Q-learning is mostly used for agricultural fields such as crop selection, crop planning process, optimizing irrigation for fields, and the use of pesticides and fertilizer. Advanced technique functions estimate the current state, Tr returns actual values, and W(ts) current state estimation. Result returns the total discount to calculate the total time.

$$G_t = T_t + \gamma T_{t+1} + \gamma^2 T_{t+2} \quad (3)$$

$$G_t = \sum_{k=0}^{\infty} \gamma^k T_{t+k} \quad (4)$$

2.4.2 Deep Q–Networks (DQN)

Deep Q-Networks (DQN) are mainly used for a smart farming technique using smart robotics for crop prediction. DQN is an

E-ISSN: 3107-5843
International Journal of Advanced Engineering and Management System
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advanced method of Q-learning. To calculate a loss function for deep Q-networks for approximate values. θ Represents a neural network. Accurate crop yield prediction

$$L(\theta) = [(r + \gamma maxQ(s', a'; \theta) - Qx(s', a'; \theta))^2] \quad (5)$$

$$Q_{target}(s, a) = r + (\gamma maxQ(s', a'; \theta^-) \quad (6)$$

Deep Q-networks for a machine learning approach for accurate crop yield prediction from soil health parameters, for advanced technology for a better solution. Q–values are taken from the DQN and reference from the neural networks to observe the current step and apply a policy for better actions obtained in each state of action. Periodically update a value in the weight in the target value in neural networks.

2.4.3 Proximal Policy Optimization

Proximal Policy Optimization is widely used for fixed and unchangeable techniques. This strategy is especially useful in an environment with is controlled by robotics. The important role of smart agricultural system and smart farming. By using Proximal Policy Optimization (PPO) policy to gradient based model.

$$L_{CLIP}(\theta) = T_e\left[\min\left(r_t(\theta)\hat{A}_t, clip(r_t(\theta), 1 - \varepsilon, 1 + \varepsilon)\hat{A}_t\right]\right. \quad (7)$$

$$\nabla_\theta J(\theta) = T_e\left[\nabla_\theta \log \pi_0 \left(a_t | s_t\right)\hat{A}_t\right] \quad (8)$$

Machine learning approaches for accurate crop yield prediction from soil health parameters to obtain a weight for the new score. rt(θ) ratio for probability by comparing the existing model with the current model and comparing how better prediction. ϵ represents a clipping parameter range values ranges from 0.1 to 0.2 minimum values update the trust values. Comparing a new model with an existing model to reduce complexity and avoid a large update breaking. Balancing the reliability of training and testing data and providing stability and evaluation metrics.

Using this evaluation model to perform (MSE) stands for Mean Square Error

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(x - \hat{y}_i)^2) \quad (9)$$

Model evaluation metrics like RMSE stand for Root Mean Squared Error

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (10)$$

Formulas to evaluate a prediction in (MAE) Mean Absolute Error

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (11)$$

To find the coefficient of determination R Square error

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y_i})^2} \quad (12)$$

3. Prediction Result and Comparative Study

The performance of the model is calculated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Coefficient of determination are calculated by using accuracy predicted by the model. The **Figure4** represent an predicted result is compared with the actual result of crop prediction using an weather report outcome of chickpea plant in the yield. The accuracy is noted by plotting a point in a charts and graph representation. Recommendation suggestion to real time

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smart agriculture for early prediction of crop yield.The **Figure5** represent an crop prediction using weather report in the outcome of rice crop in the yield the result is obtains to solve a real world problems in agriculture sector and a ability to handle a updates and complex agricultural environments. The **Figure6** represent an crop to predict an yield in the graphical representation of locational map to find the area for growing plant to balancing a parameter for early detection for planning a crop yield in a soil. The study is to estimate cost effective, resource allocation, yield estimation, smart agriculture, preplanning and sustainable farming.

Figure 3. Outcome of Chickpea plant in yield

Figure 4. Outcome of Rice crop in yield

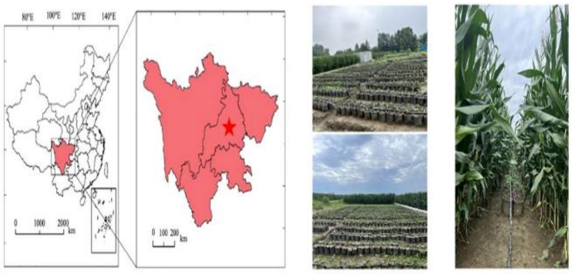

Figure 5. Graph to predict yield prediction

Parameter of soil	**Level of score**	**Yield impact**
Nitrogen (N)		Leaf growth
Phosphorus (P)	0.23	Root and flower
Potassium (K)	0.19	Affect a quality
pH levels	0.15	Nutrient level
Moisture content	0.11	Plant hydration
Organic matter	0.06	Soil fertility
Soil temperature	0.03	Affects seed

Table 1. Table for feature model

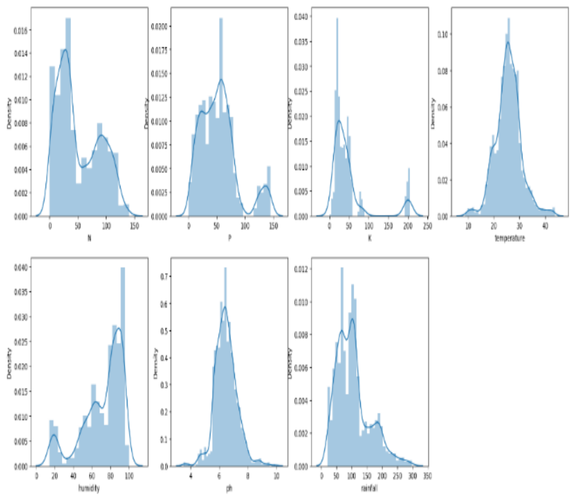

Figure 6. Plot of crop yield features

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df

	N	P	K	temperature	humidity	ph	rainfall	label
0	90	42.0	43.0	20.879744	82.002744	6.502985	203.983200	rice
1	85	58.0	41.0	22.000940	80.319644	7.038096	226.655537	rice
2	60	55.0	44.0	23.004459	82.320763	7.840207	263.964248	rice
3	74	35.0	40.0	26.491096	80.158363	6.980401	242.864034	rice
4	78	42.0	42.0	20.130175	81.604873	7.628473	262.717340	rice
...	...	...	...	...	...	...	...	...
2195	107	34.0	32.0	26.774637	66.413269	6.780064	NaN	coffee
2196	99	15.0	27.0	27.417112	56.636362	6.086922	127.924610	coffee
2197	118	33.0	30.0	24.131797	67.225123	6.362608	173.322839	coffee
2198	117	32.0	34.0	26.272418	52.127394	6.758793	127.175293	coffee
2199	104	18.0	30.0	23.603016	60.396475	6.779833	140.937041	coffee

2200 rows × 8 columns

Figure 7. Estimation of environmental and soil weather attributes

Sample data	Actual data	Predicted (PPO)	Predicted (DQN)	Predicted (Q learning)
1	3.3	3.6	3.4	3.2
2	2.7	2.9	2.8	2.5
3	4.1	4.0	3.9	3.6
4	3.0	3.2	2.9	2.7

Table 2. Table for actual vs predicted test data

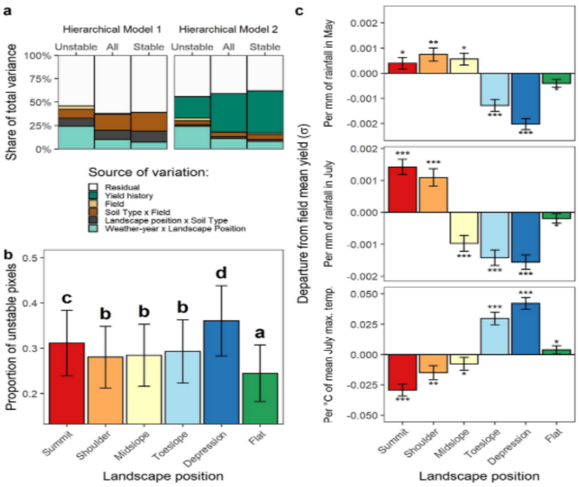

Figure 8. Yield variation over time

Methods	Training data	Stability model	Levels
Q-learning	8.6	Medium	Slow
DQN	14.3	High	Moderate
PPO	17.6	Very high	Fast

Table3. Table for stability and training data

Methods	Mean Absolute Error (MAE)	Root Mean Square Error (RMSE)	R^2 Score
Q-learning	0.74	6.3	0.79
DQN	0.52	4.8	0.89
PPO	0.44	4.2	0.92

Table 4. Table for comparison

Methods	Accuracy percentage	RMSE	Observation
Q-learning	79%	6.3	Performs better
Deep Q learning	89%	4.8	Complex data
Proximal Policy Optimization	92%	4.2	High accuracy

Table 5. Result obtained

3.1. Soil Health Parameter Summary

The summary statistics of the area under crop yield are shown in **Table 6**. An assessment of the machine learning data approaches for crop yield prediction from soil health parameters. **Tables 3,4,5** represent a dataset used for training and testing models using machine learning. This approach helps to monitor the soil parameters, crop yield prediction, ranges, and values. Soil parameters presented in the soil with standard health of crops in the yield are represented in **Figure 9**. Neutral value and pH values are closely in soil health parameters. Crop yields are affected by nitrogen, potassium, and phosphorus, with high variability. Soil temperature and moisture range affect crop yield is depending on soil conditions.

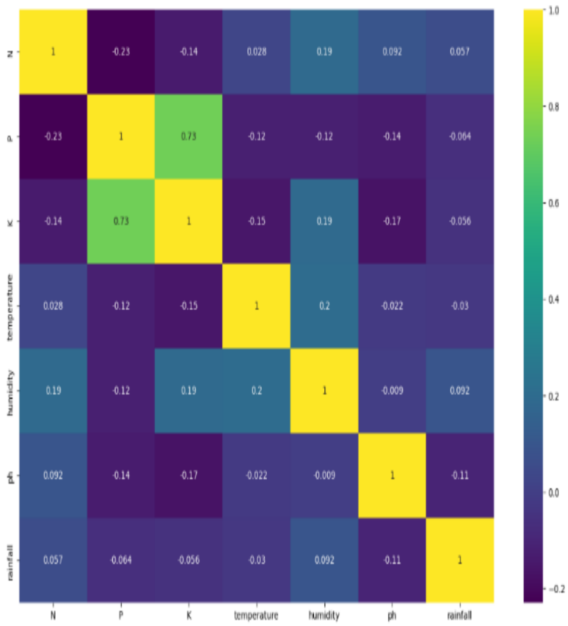

Figure 9. Correlation analysis of soil and climate factors

Data	**Minimum score**	**Maximum score**	**Mean value**	**Standard Deviation (SD)**	**Units**
pH level	4.6	8.3	6.7	0.79	pH scale
Nitrogen (N)	21	191	110.3	35.7	Kg/ha
Phosphorus(P)	6	51	29.4	9.7	Kg/ha
Potassium (K)	61	251	141	41.6	Kg/ha
Moisture content	8.1	35.1	22.8	6.8	%
Organic matter	0.7	4.3	2.2	0.9	%
Electrical conductivity (EC)	0.2	1.9	0.76	0.33	Ds/m
Crop yield	1.8	5.7	3.4	0.9	Tons/ha

Table 6. Summary statistics table

E-ISSN: 3107-5843
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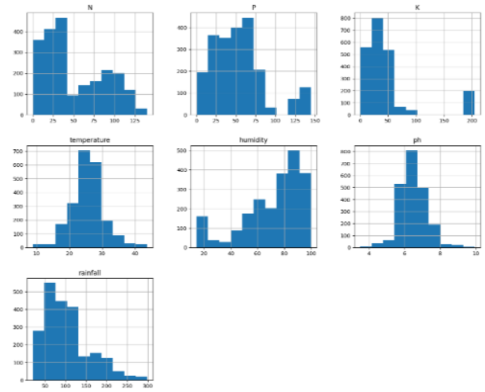

Figure 10. Chart based data analysis

water level	Classification	Crop impacts
Less than 5.5	High	Low nutrient
5.5 to 6.5	Medium	Match for most crops
6.5 to 7.5	Low	Medium for crop growth
Greater than 7.5	Alkaline	Low nutrients

Table 7. Table for classification of soil quality level

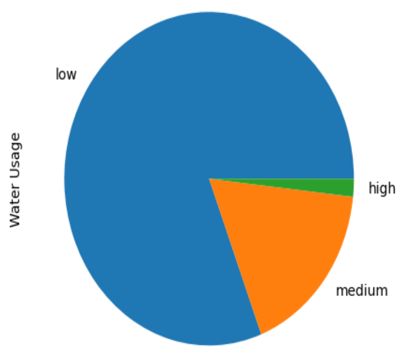

Figure 11. Water resource utilization

Table 7 summarizes the pH levels from less than 5.5 to greater than 7.5. crop impact on the lot nutrient as a classification of strongly bound with less than 5.5. Crop impacts on suitable and best match for most crops as a classification of moderate with a relationship of 5.5 to 6.5. **Figure 11** represents that water usage is low, medium, and high crops impact, as moderate for crop growth, with a separation of neutral with a 6.5 to 7.5 relationship on pH level. Crop impact as a classification of alkaline as a relationship greater than 7.5 level.

Type of crop	Nitrogen (N)	Phosphorus (P)	Potassium (K)	yield
Rice	126	31	141	4.2
Wheat	141	29	161	4.6
Maize	96	26	131	3.9

Table 8. Table for soil nutrient level

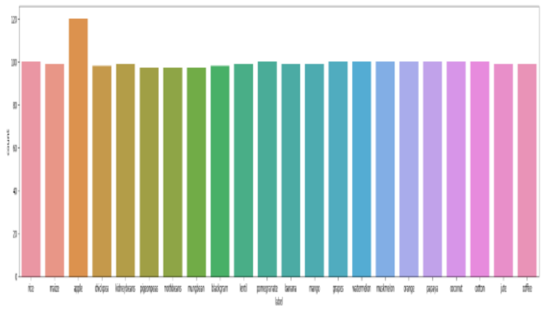

Figure 12. Value count bar chart

Table 8 summarizes the average level for each region in the crop yield to find the status of nutrients present in the soil. There are various types of crops like rice, wheat, maize, etc. The region, such as Tamil Nadu for rice cultivation, Punjab for wheat cultivation, Karnataka for maize cultivation, so these types of crops can be grown in the location for better profit. The parameters present in the soil are nitrogen, Phosphorus, and potassium for crop growth in the soil **Figure 12**.

Error range	**Q-learning**		**Deep Q networks**	**Proximal policy optimization**
<0.5	13		19	24
0.5 to 1.0	23		28	31
>1.0	17		6	3

Table 9. Table for error distribution

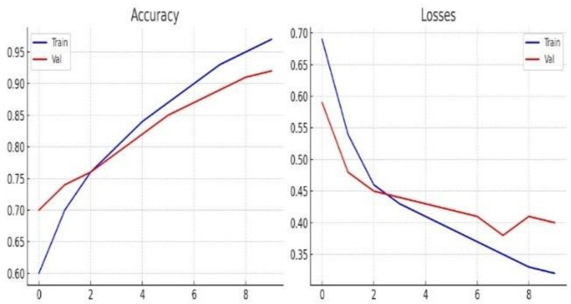

Figure 13. Graph for Accuracy and Loss

Table 9 summarizes Q-learning, Deep Q networks, and Proximal policy optimization with error distribution of values. Q-learning determines learning rate, factor of discount, and rate of exploration. Deep Q-learning networks (DQL) determine epsilon decay and replay buffer. **Figure 13** represents the size of the batch and the rate of learning. Proximal Policy Optimization for gamma function, learning rate, and clip range function. These algorithms are used for finding an error detection in the range of greater than 0.5 to less than 1.0 with the technical samples.

4. Conclusion

As a model predicted accuracy for Q-learning 78%, Deep Q-networks 88% and Proximal Policy Optimization (PPO) 91% with a high accuracy model. The performance of these models is good in both training and testing. Good model for reliability and model evaluation in prediction for error handling. High accuracy compared to other models by using the core of the machine learning concept. To visualize a model action on a real-time complex problem. By comparing actual data with the predicted data, the crop yield prediction using the PPO model for high accuracy. Using machine learning approaches for accurate crop yield prediction from soil health parameters gives 91 percentage of high accuracy predicted by the model. An ML model can predict a crop yield more accurately than the best result obtained. Soil and climate prediction are accurately integrated by climate change forecasting parameters. Reduce manual error, time consuming can be handled by the model to enable real-time monitoring, detect diseases, and a better decision-making process.

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