

Design of BQN-based decision support system and HSCNN-GPOR futuristic prediction for precision agriculture using IoT

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Abstract

Precision agriculture (PA) makes use of technology to increase sustainability by making better use of resources like land, water, fuel, fertilizer, and pesticides. In PA, crop productivity and profitability are impacted by weather, fertilizer usage, pests, crop irrigation, and crop diseases. In many existing techniques, there is no effective irrigation control and futuristic prediction of diseases in crops and soil fertility. To overcome this issue, a novel Bayesian Q-Network (BQN)-based decision support system and Hopfield symmetric convolutional neural network-Gaussian probabilistic ordinal regression (HSCNN-GPOR) have been proposed, for effective decision-making and futuristic prediction and classification of diseases in crops. In this technique, a decisive logistic associative rule-based BQN model has been introduced to overcome the weak integrated decisions and an inter-temporal comparison of soil fertility and environmental information. This technique is used to obtain the soil fertility and to improve the intertemporal characteristics by Fuzzy logistic associative rule to obtain environmental information. In this existing model, to make a decision-making process, BQN has been introduced, to improve the intertemporal characteristics to make an effective decision for irrigation control and fertilizer usage. Moreover, the existing techniques predict crop diseases and pests from collected crop images, but they do not predict the future condition of crops from these crop images. Hence, a model Hopfield Symmetric CNN-GPOR has been introduced to classify pests and predict future diseases in crops. In this model, a symmetric Hopfield CNN extracts features from crop images, which are then utilized by Gaussian Probabilistic Ordinal Regression to classify crop diseases and pests, along with future predictions. Therefore, the proposed model provides the ability to make wise decisions, futuristic predictions of diseases in crops, and classify the pests in crops with high recognition, accuracy, and classification rates.

Keywords

fertile soil, water irrigation, fuzzy logic associative rule, Bayesian Q network, crop health monitoring

1. Introduction

In precision agriculture (PA), weather, fertilizer application, crop irrigation, crop diseases, and pests

affect crop productivity and profitability. To control the use of fertilizer and crop irrigation, as well as to offer alerts regarding weather conditions, various decision support systems have been utilized.

However, the current decision support systems only evaluate one set of choice sets at a time, ignoring realistic correlations and the relative scalability to descriptor variables, which results in weak intertemporal comparison and is unsuitable for large embedded judgments. Furthermore, current techniques for predicting crop diseases and pests do not concentrate on future predictions from crop images, and the detection network needs a lot of annotation data for pixel-by-pixel labeling, which raises the cost. Additionally, the recognition rate is decreased due to the presence of occlusion and dense blade overlap, which decreases prediction and classification accuracy. As a result, a novel strategy must be suggested to provide an effective Decision Support System with a futuristic forecast of crop diseases in PA.

PA is the science of improving crop yields and assisting management decisions using high-technology sensors and analysis tools. The goal of precision farming is to improve agricultural yield and reduce potential environmental risks. In general, the agriculture sector employs over 60%–70% of India's workforce [1]. This is due to the high soil fertility and extensive network of irrigation water sources. The great availability and production of flora are ensured by the varied nature of climatic conditions across different sites. In India, there are over a 100 different crops grown across the country. To make it easier to understand and visualize these crops, they've been divided into categories [2]. Despite the presence of resources, they do not yield results that are comparable to their availability. It is due to the lack and inefficient use of technology, the lack of education and awareness among agrarians, and the employment of some antiquated ways [3, 4].

Climate change is the fundamental determinant of agricultural productivity; it has an impact on crop production and has an impact on available water resources and soil qualities, since it is very difficult to grow crops by understanding weather conditions. Weather plays a significant effect in agricultural production. Crops are more frequent in weather-based frangible agriculture systems in general [5, 6]. Crop irrigation and fertilizer usage are also playing a vital role in crop growth and yield. Hence, an agricultural decision support system (ADSS) is developed which is a human–computer system that uses data from a variety of sources to provide farmers with a list of recommendations to aid their decision-making in a variety of situations. One of the most distinguishing features of an ADSS is that it does not provide direct orders or commands to farmers. By monitoring crop

growth rates, ADSS can recommend the ideal times for irrigation, fertilization, pollination, and harvesting. According to statistics, yield output can be estimated with 95% accuracy, and productivity can be boosted by up to 30%. The digital farming system's drawback is that it only considers greenhouse and large-scale row crop scenarios. As a result, its more intriguing weather can enhance the system's capability to provide farmers with sufficient solution suites [7–9]. A linear model is used in ADSS to examine the trade-off among economic, social, and environmental objectives based on environmental indicators. Farmers may control and monitor irrigation processes directly using a user-friendly graphical interface. DSIRR requires additional development, such as adopting modular techniques to allow the integration of new modules focused on specific features of interest, although water usage is greatly decreased and farmers can irrigate farming fields more efficiently [10, 11].

Crop production losses owing to pests and diseases are significant, especially in the semi-arid climate of India. Crop diseases cause a significant reduction in throughput. Insects, pests, viruses, animals, and weeds are responsible for between 20% and 40% of global agricultural production yield depletion. They also have some features, some of which have short-term and others of which have long-term implications for global food security. One of the most important study areas in PA is identifying illnesses from images of plant leaves. Image processing and the latest Neural Network research can considerably improve plant development and protection techniques with more computing power [12, 13]. For identifying and classifying plant diseases, a variety of artificial intelligence (AI) technologies is used. Neural networks, logistic regressions, decision trees, support vector machines (SVM), k-Nearest Neighbors (k-NN), Naive Bayes, and deep convolutional neural networks (deep CNN) are the most commonly used AI methodologies for the identification of diseases [14, 15]. However, the existing ADSS and ML techniques are not suitable for large integrated decisions and reduce the recognition effect during the prediction of disease and pests. Hence, it is necessary to develop a novel approach to improve soil fertility and water irrigation and predict future diseases and classify pest in crops for PA. Major contributions in this study are given as follows:

- To overcome the limitations of environmental factors, diseases, and pests in crops and provide effective decision-making in PA a Bayesian Q-Network (BQN)-based Decision Support

System and Hopfield symmetric convolutional neural network-Gaussian probabilistic ordinal regression (HSCNN-GPOR) technique has been introduced for improving the environmental factors and effective irrigation control, and also predict the futuristic disease in crops.

- For the improvement of fertilizer and irrigation by enhancing intertemporal features in PA a unique technique, decisive logistic associative rule-based BQN has been presented, which enhances the performance of decision-making for irrigation control.
- To categorize agricultural pests and predict future crop diseases, a new Hopfield Symmetric CNN-GPOR has been utilized to anticipate and classify the futuristic diseases and pests in crops.

These contributions, which were mentioned above, are used to provide irrigation control and predict the futuristic disease in plants and pests. Section II describes the literature survey, Section III describes the proposed methodology and its working process, and Section IV discusses the proposed model evaluation and performance. Finally, Section V concludes the paper.

II. Literature Survey

Campoverde et al. [16] proposed a system to manage agricultural operations in terms of irrigation using Internet of Things (IoT) sensors and smart platforms such as Raspberry Pi and Arduino. Two fundamental criteria influence the management of irrigation water pumps: soil moisture and evapotranspiration. To learn the correct water amount required by the plants, the system employs a reinforcement learning (RL) approach based on the Markov Decision Process. This method allows for a reduction in both water and energy usage. The concept was contrasted to a traditional irrigation system, which is typically based on a soil humidity threshold and makes decisions based on that setting. Although, this model becomes impractical for decisions that occur repetitively over time.

Lizana et al. [17] introduced a sensing/actuation station based on commercial off-the-shelf hardware, and a mobile application for remote user interaction makes up the fundamental design. The system's usage of a legacy text messaging service to enable warning and control operations for monitoring and irrigation is a crucial feature. Without the requirement for new network infrastructure, this capability permits widely available and highly stable communications

between the field station and faraway users. In a small open-field area for tomato cultivation, a functional prototype of the system was tested to evaluate its efficacy. However, crop disease and pest prediction are not provided in this model.

Franceschelli et al. [18] showed the electronic architecture of a portable and non-invasive soil moisture device based on an open rectangular waveguide. An embedded predictive model, based on a partial least squares (PLS) regression tool, elaborates on the spectral information, measured in the range of 1.5–2.7 GHz, for the estimation of soil moisture (percent) in a real setting. A waveguide with Tx and Rx antennae, as well as an electronic circuit controlled by a microcontroller, make up the proposed system. It will be demonstrated how the method gives a meaningful and quick estimation of moisture on silty clay loam soil with a moisture range of 9%–32% and a soil temperature of 8–18°C. Even though this model ignores genuine relationships and sensitivity to descriptor variables' relative scalability.

Nie et al. [19] presented a disease detection network based on Faster R-CNN and multi-task learning to identify strawberry verticillium wilt. The strawberry verticillium wilt detection network (SVWDN) employs attention mechanisms in the disease detection network's feature extraction. The symptoms of discovered plant components are used by SVWDN to detect verticillium wilt. In comparison to previous methods for identifying disease based on the overall appearance of the plant, the SVWDN identifies the petioles and young leaves automatically when assessing whether the strawberry has verticillium wilt. However, the network design is completed and requires a lot of annotation information.

Zhang et al. [20] presented an enhanced multi-task cascaded convolutional network-based intelligent fruit detection approach. This technology allows the Auro to work in real-time and with high precision. Furthermore, this research proposes an improved augmented technique based on image fusion to improve detector performance, considering the relationship between the diversity samples in the dataset and the parameters of neural networks' evolution. However, there is a need to create a more acceptable and effective network model for recognition. In addition, enhancing and optimizing the detector's accuracy is a vital goal for the future.

Clark et al. [21] examined the determinants of farmers' adoption of PA technologies in cropping systems. The findings demonstrated that some factors significantly influence farmers' intentions to adopt PA, including perceived need for technology

characteristics (PNTC), perceived benefits, perceptions of the effectiveness of facilitating conditions, and perceived risks of adoption. However, to ensure the effective coproduction of PA technologies during the innovation phase, to guarantee that PA technologies are in line with the final objectives, it offers suggestions for future technology promotion.

Torky et al. [22] presented a thorough analysis of the significance of combining blockchain and IoT for creating smart apps for PA. Also, addressed a few of the concerns with blockchain openness, security, and privacy that prevent the development of blockchain-IoT systems for PA. However, additional research is required to examine the relationship between blockchain and IoT in greater detail concerning use cases for PA technologies.

Sahu et al. [23] explored the key factors affecting the effectiveness of deep neural networks for detecting plant diseases. The use of DL approaches to identify and categorize plant diseases may be affected by many aspects and difficulties, which are highlighted in this work. The study's issues are based on research in the field as well as studies done using an image database that has about 1,296 pictures of bean crop leaves. However, the research needs to be improved to make predictions about plant disease in the future.

Akhter et al. [24] identified the strengths and potential of computing methods used in agriculture, such as wireless sensor networks, the IoT, data analytics, and machine learning. The research provided a prediction model for apple disease utilizing data analytics and machine learning in an IoT system in Kashmir Valley apple farms. To enhance the amount and quality of crop production from the fields to satisfy the rising food demand, the agriculture industry will reap new benefits from the application of machine learning employing IoT data analytics. However, the work will be expanded to include additional crop-influencing factors.

From the analysis, [16] is not suitable for large embedded decisions, and [17] does not focus on the prediction of diseases and pests [18] ignoring the scalability of descriptor variables and real correlations, and [19] requires more information about the input [20] need to optimize detector accuracy [21] provides suggestions for developing technology [22] need to build a relationship between blockchain and IoT in PA [23] need to improve the prediction of disease in the future [24] to expand the technique to detect disease in plants.

III. Design of BQN-Based Decision Support System and HSCNN-GPOR Futuristic Prediction for PA Using IoT

Crop productivity and profitability in PA are impacted by the weather, fertilizer application, crop irrigation, crop diseases, and pests. In existing techniques, there is no accurate prediction of crop diseases and classification of pests from collected crop images. To improve the application of fertilizer and agricultural irrigation, multiple decision support systems have been utilized to notify about meteorological conditions. However, traditional decision support systems only take into account one attribute parameter when making multi-criteria decisions, which leads to poor inter-temporal performance and makes it challenging to make decisions for large embedded datasets. The proposed design of the BQN-based decision support system and HSCNN-GPOR has been introduced to improve the soil fertility and environmental factors for water irrigation and to predict future problems or diseases and classify the pests in crops for PA using the IoT. For this purpose, by using IoT sensors, datasets are collected from the agricultural field. A decisive logistic associative rule-based BQN has been proposed to obtain adequate parameters of soil and environmental information extract the relationship and localize data segments by using a fuzzy logistic associative rule with a correlation coefficient. The extracted data segments are then parallelized lattice distribution of frequent item sets to enhance the support of large embedding decision-making. To improve the performance of multi-functionality in decision making by BQN, which utilizes the continuous Dirichlet multinomial distribution of weighted parameters, which improves the inter-temporal characteristics, and to make effective decisions on the use of fertilizer and irrigation.

Furthermore, the existing prediction system needs more annotation information for the pixel-to-pixel class labeling due to the presence of occlusion and dense blade overlap which leads to an increase in cost and low recognition rate, which reduces the accuracy of prediction and classification. Hence, a technique HSCNN-GPOR has been introduced for predicting the future condition of crops and classifying the pests from the crop images. Using Hopfield Symmetric CNN with depth-wise spatial and point-wise channel convolutional layers, existing features, along with swell, edge burn, and spots, are retrieved

from the image to maximize identification rate in occlusion and overlap with deep extraction of spatial and channel properties. The necessity for annotation data in pixel-to-pixel labeling is eliminated by the symmetric bidirectional connected network in HSCNN, and the regularization principle and probabilistic determination of the covariance function of ordinal variables, Gaussian Probabilistic Ordinal Regression (GPOR), uses extracted characteristics to perform illness and pest categorization and futuristic prediction. Hence, the proposed system provides multi-criteria decision-making and provides effective futuristic prediction with a high recognition rate, cost-effectiveness, and high classification accuracy.

Figure 1 illustrates the process flow for the proposed system, in which the data has been collected from the agricultural field using IoT sensors. First, checking the environmental contents in agriculture by using fuzzy logic associative rules and making an efficient decision by using the BQN. Again, a sample from the cropped image is taken and by using the Hopfield symmetric CNN technique, it detects whether the crop is affected by the disease or not and identifies the disease in crops. To predict the futuristic disease in crops GPOR technique is used.

a. Decisive logistic associative rule-based BQN

The BQN-based system merges Bayesian inference and RL to facilitate effective decision-making in dynamic environments. Bayesian inference models uncertainty by continuously updating probabilities with new data, enhancing predictions in uncertain situations. RL enables the system to learn optimal actions over time by receiving feedback from its environment, improving strategies through trial and error. This integration allows the system to optimize real-time decisions, such as in irrigation and pest control. By combining both methods, the BQN system adapts to changing conditions, refining its decisions for long-term benefits. To enhance soil fertility and environmental factors for water irrigation, a Decisive Logistic Associative Rule-based BQN has been introduced. This method generates soil and environmental data through associative rule generation based on a logistic transform. It uses correlation coefficients to identify relationships and localize data segments, incorporating scalable descriptor variables and parallelized lattice distribution of frequent item sets for more efficient decision-making. As a

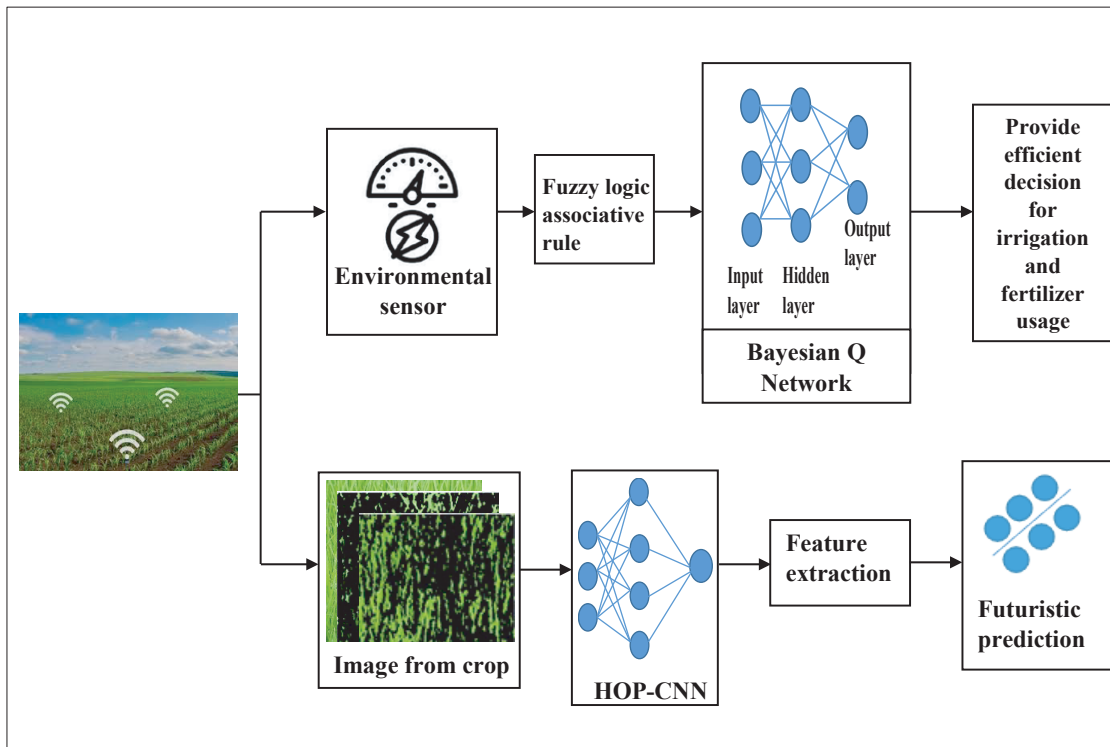


Figure 1: Architecture diagram for the proposed design of BQN-based decisive supporting system and Hopfield Symmetric CNN-GPOR. BQN, Bayesian Q-Network.

result, it facilitates large-scale embedded decision-making. Similar to this, the BQN uses continuous Dirichlet to deliver multi-functionality performance in decision-making. Figure 2 illustrates the process flow for the decisive logistic associative rule-based BQN.

The soil quality report also shows the various crops grown in the field by the farmers as well as the location's latitude and longitude. First, take the sample dataset from the soil content and environmental factors. From this, the associative rule for the sample dataset is determined in Eq. (1) as

$$A = \{A_j^i | i = (i_1, i_2, i_3) = I; j = (j_1, j_2, j_3) = J\}. \quad (1)$$

From Eq. (1), I is the soil fertility parameter, and i_1 , i_2 and i_3 represent the content of nitrogen, phosphorous, and potassium in soil fertility. J is environmental factor, and J_1 , J_2 , J_3 and J_4 represent the factors of temperature, humidity, pH value, and rainfall level. A_j^i is the relation of both soil and environmental factors. The objective of the fuzzy logic-based associative rule is to analyze A and obtain a list of data segments in terms of soil fertility and environmental factors. By applying the fuzzy logic-based associative rule, it extracts the relationship between data segments in the dataset and the required parameter.

Moreover, the BQN model has been introduced to provide the final decision to maintain soil fertility and water irrigation. The BQN agent engages in interactions with the environment and the soil parameters. With the input of the soil and the environment parameters that is nitrogen, phosphorous, and potassium are the factors of soil fertility, and temperature, humidity, pH value, and rainfall are environmental factors. The

network generates Q values for each activity carried out within the action space. The BQN's objective is to detect and improve parameters. This model is used in the prediction process to identify the best decision that occurs in the dataset. The BQN is utilized with continuous Dirichlet multinomial distribution. The multinomial distribution is the binomial distribution's multivariate generalization used to define counts of binary outcomes. This concept is expanded by the multinomial distribution to include more than two distinct outcomes. Q-Learning with Continuous Dirichlet Multinomial Distribution establishes the best final decision for the chosen parameter, which chooses the most efficient decision. To keep the soil fertile and the water level appropriate for irrigation control, the best choice is provided by this Decisive Logistic Associative Rule-based BQN. Moreover, to effectively classify crop diseases with futuristic prediction, Hopfield Symmetric CNN-GPOR has been used, which is explained in the next subsection.

b. Hopfield Symmetric CNN-GPOR

The HSCNN-GPOR model is a hybrid approach that combines Hopfield Symmetric Convolutional Neural Network (HSCNN) and GPOR to enhance prediction and classification tasks, particularly in complex fields like crop disease detection and pest classification. The HSCNN leverages convolutional layers integrated with Hopfield networks, enabling bidirectional connections for improved feature extraction and resilience against occlusions and noise. Meanwhile, GPOR applies probabilistic reasoning to perform ordinal classification, effectively handling

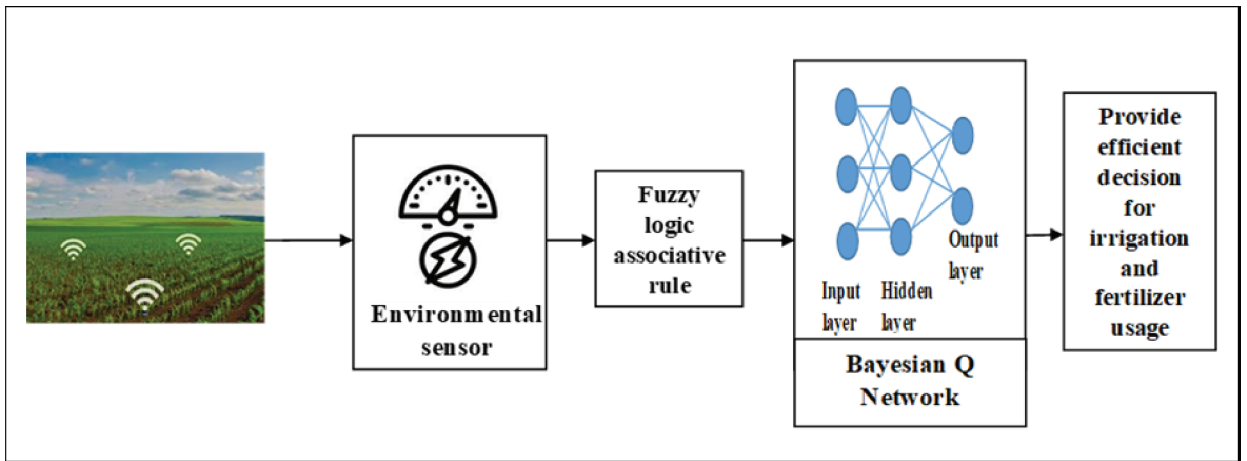


Figure 2: Process flow for decisive logistic associative rule-based BQN. BQN, Bayesian Q-Network.

varying levels of severity. For crop disease prediction and pest classification, a novel HSCNN-GPOR framework is introduced, which extracts essential features such as texture, color, shape, correlation, energy, and skewness. Additionally, it captures specific crop conditions, including bacterial slime, black spot, powdery mildew, downy mildew, blight, canker, and edge burn, using depth-wise spatial and pointwise channel convolutional layers within the HSCNN architecture. The symmetric bidirectional connected network in Hopfield Symmetric CNN removes the need for annotation data in pixel-to-pixel labeling. To find the disease in crops GPOR method is used, this method uses extracted characteristics to perform futuristic prediction and categorize disease and pests utilizing regularization property and probabilistic determination of covariance function of ordinal variables.

Moreover, to predict future disease in plants, a novel GPOR technique is used and utilizes Hopfield Symmetric CNN to extract from the image features like color shift, sports, edge burn, and swell. Occlusion and blade overlap are reduced with the use of depth-wise spatial and pointwise channel layers for feature extraction, which is accomplished using a deep enhanced convolutional layer. The equation for calculating the affected area in crops and identifying the pests has been mentioned in Eq. (2),

$$F = \sum_{i=1}^n \sum_{j=1}^m g(i, j) \quad (2)$$

where F denotes the affected area in crops and also identifies the pests and where n, m is the image coordinate value and $g(i, j)$ is a binary image function, in which it identifies the disease in crops like fungi, bacteria, viruses, and protozoa, as well

as insects and parasitic plants and also identifies the pests like insects, nematodes, mites, snails, slugs, and vertebrates like rats, birds. This model is coupled in a symmetric bidirectional linked network connection to minimize the amount of annotation information needed during the pixel-to-pixel labeling process. Gaussian Ordinal regression calculates the covariance function of all potential ordinal variables and uses their regularization property to determine the condition of crops. Figure 3 illustrates the process flow of Hopfield Symmetric CNN and GPOR.

Figure 4 illustrates the architecture of Hopfield symmetric CNN, in which the crop image is given as the input layer and then the features such as color, texture, shape, and correlation are extracted by using HOPCNN. The extracted features are then used to classify pests like nematodes, mites, snails, and slugs, and diseases in plants like bacterial blight, blast brown spot, and tungro.

Figure 5 illustrates the process flow of the proposed BQN-based decisive logistic transformation and Hopfield Symmetric CNN-GPOR. Firstly, data are collected by the IoT sensors. Also, soil and environmental factors are obtained by a fuzzy logistic associative rule, and then extracting the data segments using the correlation coefficient. As a result, it facilitates extensive embedded decision-making by parallelized lattice distribution. Similar to this, BQN provides multi-functionality performance in decision-making by applying continuous Dirichlet multinomial distribution, which enhances inter-temporal characteristics to make smart decisions on the use of fertilizer and irrigation. Moreover, crop images require annotation data for disease and pest prediction. Hopfield Symmetric CNN is used to extract swell, edge burn, and spots from images. Utilizing

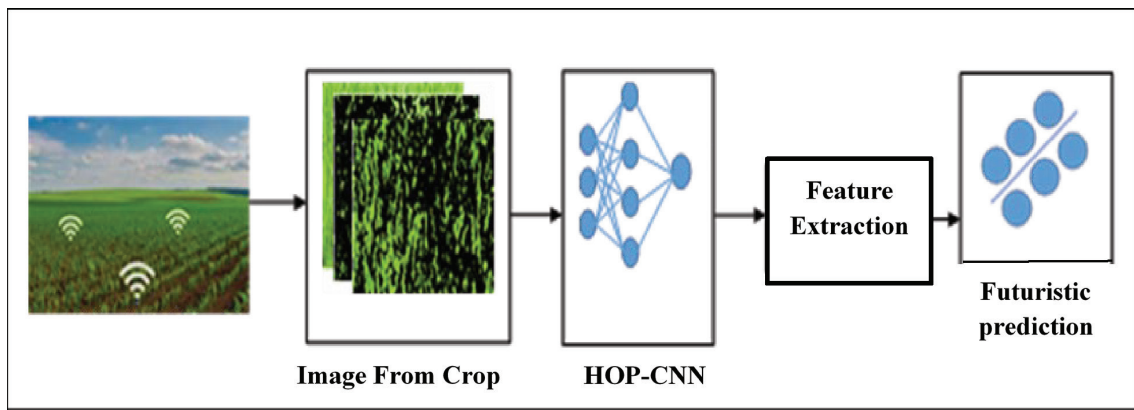


Figure 3: Process flow for Hopfield Symmetric CNN-GPOR.

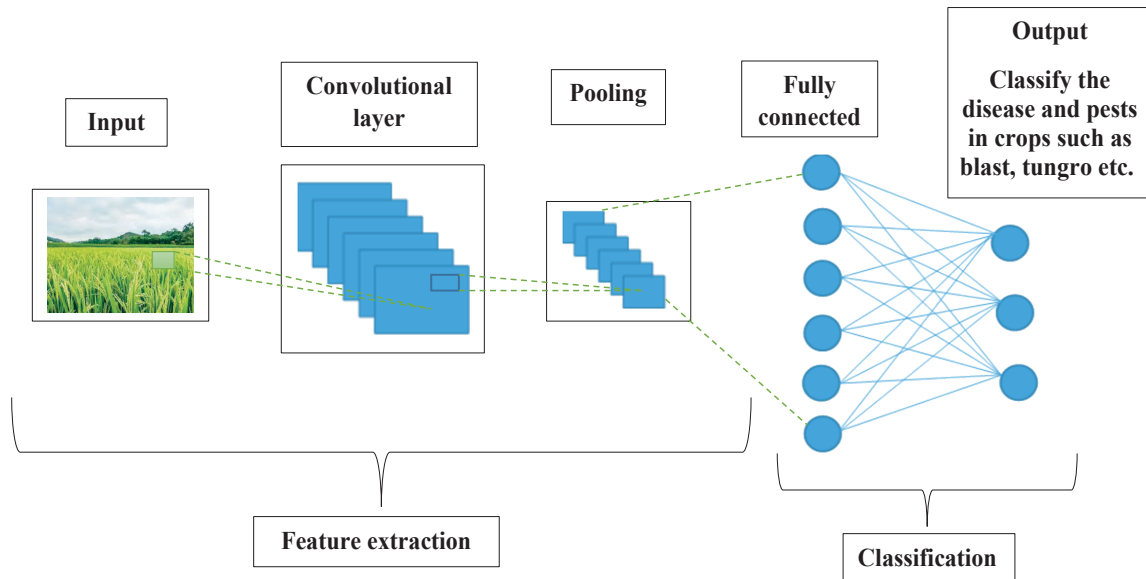


Figure 4: Hopfield Symmetric CNN architecture.

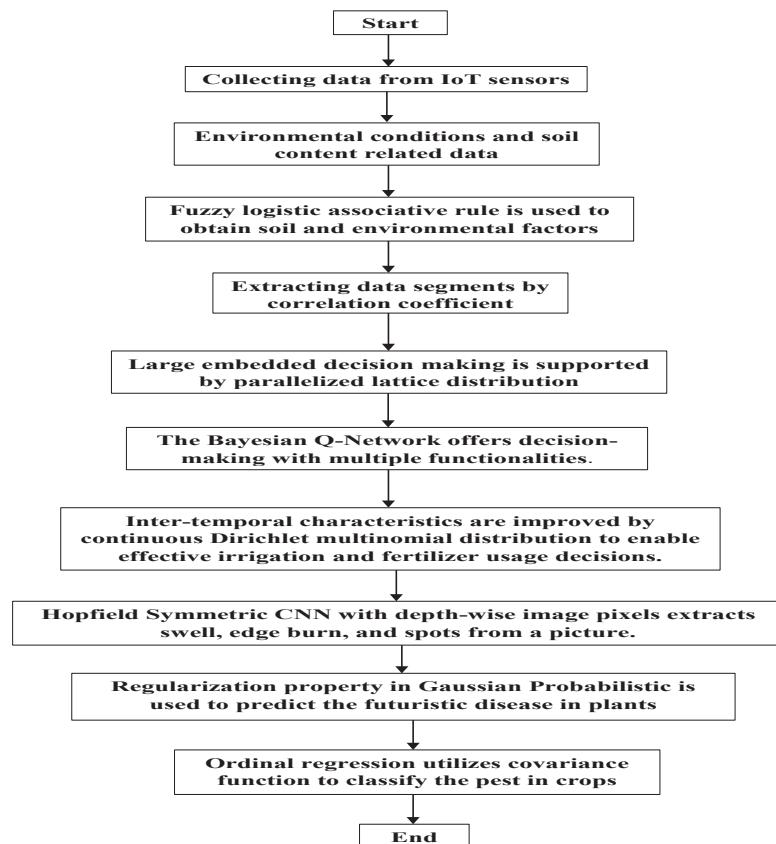


Figure 5: Flowchart for the proposed design BQN-based decisive logistic transformation and Hopfield symmetric CNN-GPOR. BQN, Bayesian Q-Network.

the regularization principle and probabilistic determination of the covariance function of ordinal data, GPOR uses the extracted features to perform illness and pest categorization and also for futuristic prediction in crops.

Overall, the proposed BQN-based Decision Support System and HSCNN-GPOR provide effective decision-making and futuristic prediction and classification of diseases in crops. The Decisive Logistic Associative Rule based BQN is used to obtain adequate parameters for soil fertility and environmental factors through a fuzzy logistic associative rule with a correlation coefficient, and to support large embedded decision-making, parallelized lattice distribution is utilized. The multi-functionality performance is improved by decision-making using BQN with Continuous Dirichlet Multinomial Function. Moreover, Hopfield symmetric CNN is utilized to extract features from the crop images, and GPOR is used to predict the futuristic disease and classify the pests in crops. The result of the proposed BQN-based Decision Support System and HSCNN-GPOR is explained in the next section.

IV. Result and Discussion

This section provides a detailed description of the implementation results and the performance of the proposed system to ensure that the proposed technique performs better and provides an accurate futuristic prediction of disease in crops.

a. Experimental setup

The experiments in this study were conducted using the MATLAB platform. The system specifications used for the simulation are outlined below:

- **Platform:** MATLAB
- **Operating System (OS):** Windows 10
- **Processor:** 64-bit Intel Processor
- **Random Access Memory (RAM):** 8 GB.

b. Performances metrics of the proposed system

The Performance metrics of the proposed BQN-based decision support system and HSCNN-GPOR for effective decision-making and to predict the futuristic disease and classify the pests in crops, and the achieved outcome were explained in detail in this section.

Figure 6 illustrates the performance of mean absolute error (MAE) in the proposed system. Similarly, the proposed system ranges the values between 9.57% and 9% with the epoch ranges from 100 to 500 respectively. Moreover, when the epoch range is maximum, the proposed system's MAE value attains a minimum value. The MAE is decreased by the Decisive Logistic Associative Rule based BQN by the fuzzy logistic associative rule that efficiently obtains the adequate parameters of soil fertility and environmental factors without any loss.

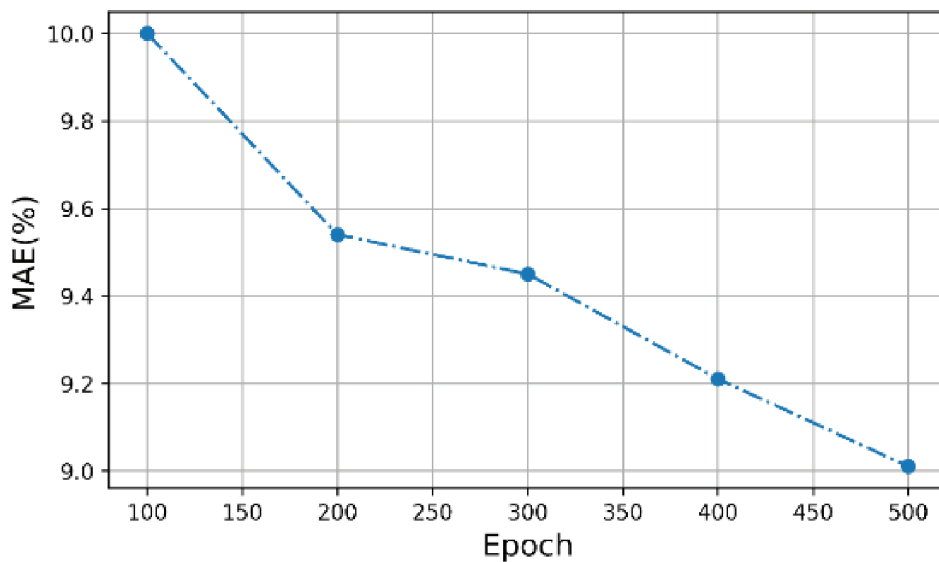


Figure 6: Performance of MAE in the proposed system. MAE, mean absolute error.

Figure 7 illustrates the performance of root mean square error (RMSE) in the proposed system. The proposed system ranges the value between 10% and 9.2% with the epoch ranging from 100 to 500. Moreover, when the epoch range is high, the proposed system RMSE value attains a minimum value. The RMSE is decreased by the decisive logistic associative rule-based BQN, which supports large embedded decision-making by parallelized lattice distribution without any loss.

Figure 8 illustrates the performance of accuracy in the proposed system. Similarly, when the epoch range is from 100 to 500, the proposed system attains the value of 96.55%–98.17%. Moreover, when the epoch level is high, the accuracy value attains the maximum value. The accuracy of the proposed BQN-based decision support system and HSCNN-GPOR is increased when compared to the other existing techniques. The proposed model attains high accuracy for effective decision-making. The accuracy performance that results from this evaluation is obtained.

Figure 9 illustrates the performance of the loss in the proposed system. Similarly, when the epoch range is from 100 to 500, the proposed system attains the value of 4.17%–3.65% respectively. Moreover, when the epoch level is high, the loss value for the proposed system attains the minimum value. Utilizing Hopfield Symmetric CNN, the performance of the loss is decreased for the image features retrieved from it. Since the loss percentage is very low, then it is more efficient to extract the features from the crop image.

Figure 10 illustrates the performance of the detection time in the proposed system. The detection time ranges between 6.13% and 6.89%, with the

epoch level ranging from 100 to 500, respectively. When the epoch level is maximum, the detection time of the proposed system achieves a maximum value of 6.89%. The detection time is increased for the proposed BQN-based decision support system and Hopfield Symmetric CNN-GPOR to predict the futuristic disease in crops more efficiently.

Figure 11 illustrates the performance of the detection rate in the proposed system. When the epoch range is from 100 to 500, the proposed system attains the value of 97.23%–97.98%, respectively. Similarly, when the epoch level is high, the detection rate for the proposed system is increased. For the classification of pests in crops, the detection rate is maximized when the epoch level is high in the proposed BQN-based decision support system and Hopfield Symmetric CNN-GPOR.

Figure 12 illustrates the performance of R^2 in the proposed system. The proposed system ranges the value between 2.47 and 0.46 with the epoch ranging from 100 to 500. Moreover, when the epoch range is high, the proposed system's R^2 value attains a minimum value. The Bayesian approach in the Q-network minimizes prediction errors by probabilistically adjusting its predictions based on observed data. It improves the model's performance through updates that reduce uncertainty in prediction outcomes, which directly contributes to higher R^2 values.

Figure 13 illustrates the performance of precision in the proposed system. Similarly, when the epoch range is from 100 to 500, the proposed system attains the value of 89.35%–96%. Moreover, when the epoch level is high, the precision value attains the maximum value. Symmetric CNN-GPOR is likely to

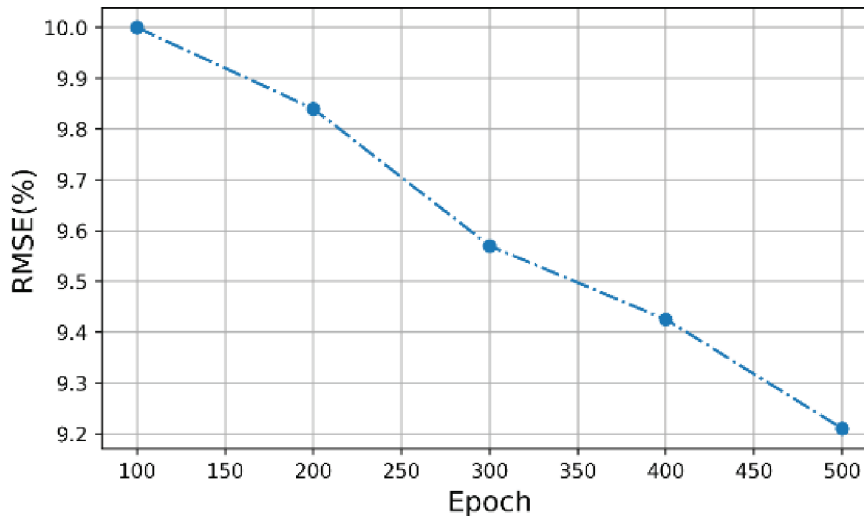


Figure 7: Performance of RMSE in the proposed system. RMSE, root mean square error.

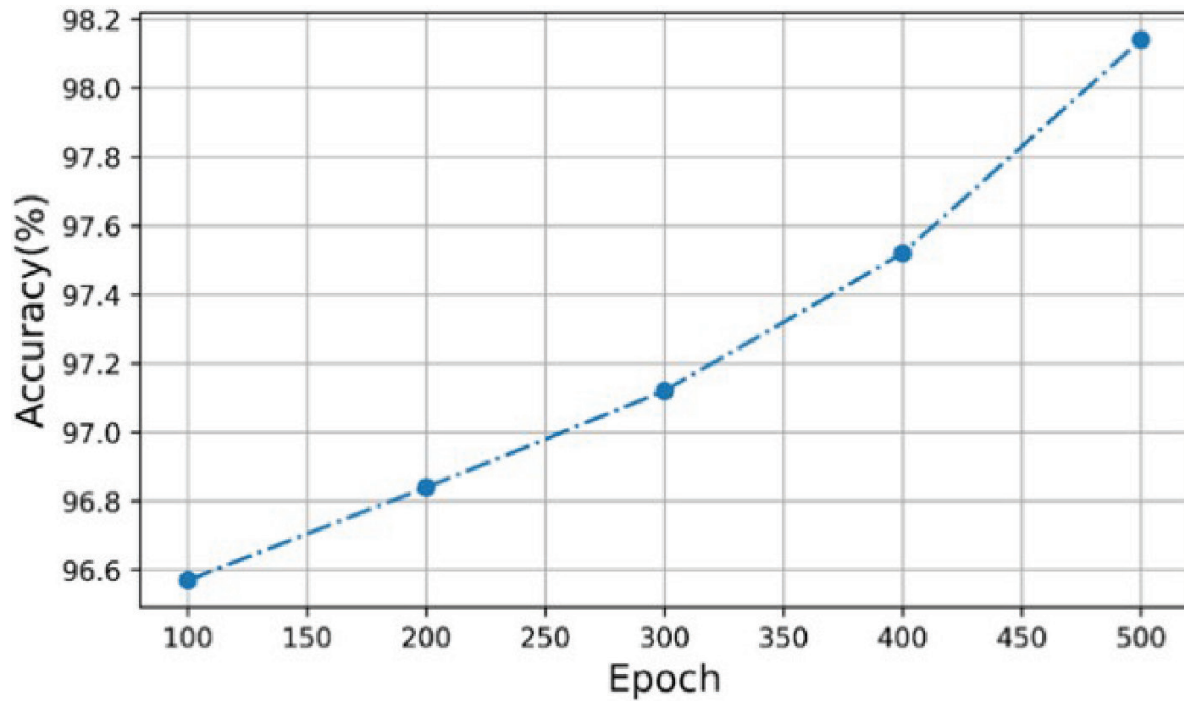


Figure 8: Performance of accuracy in the proposed system.

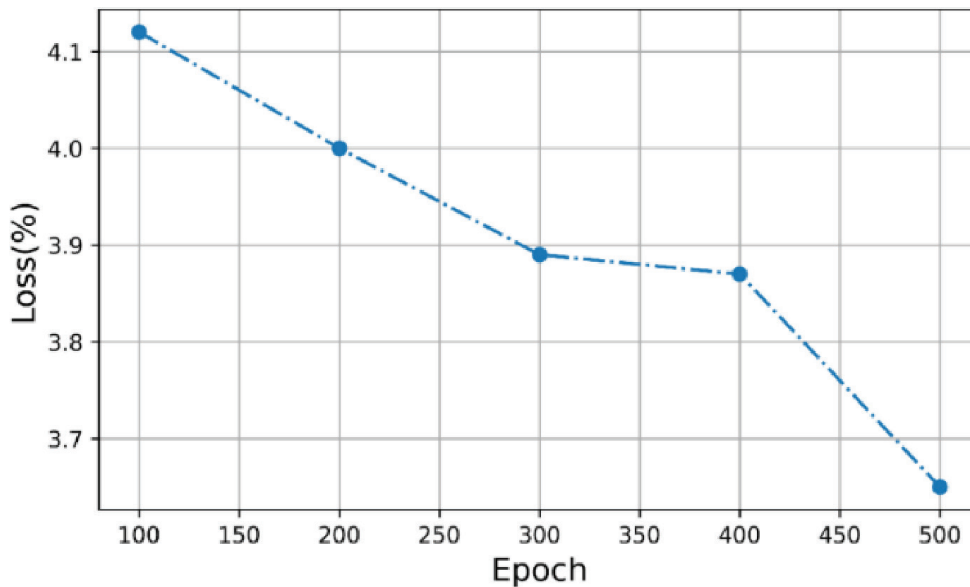


Figure 9: Performance of loss in the proposed system.

be applied in tasks such as image regression, where it can enhance precision by learning highly complex patterns from the input data. The CNN component helps the model to capture spatial and hierarchical relationships, while the GPOR part (generalized

polynomial regression) fine-tunes these relationships to ensure more accurate predictions.

Figure 14 illustrates the performance of Recall in the proposed system. Similarly, when the epoch range is from 100 to 500, the proposed system

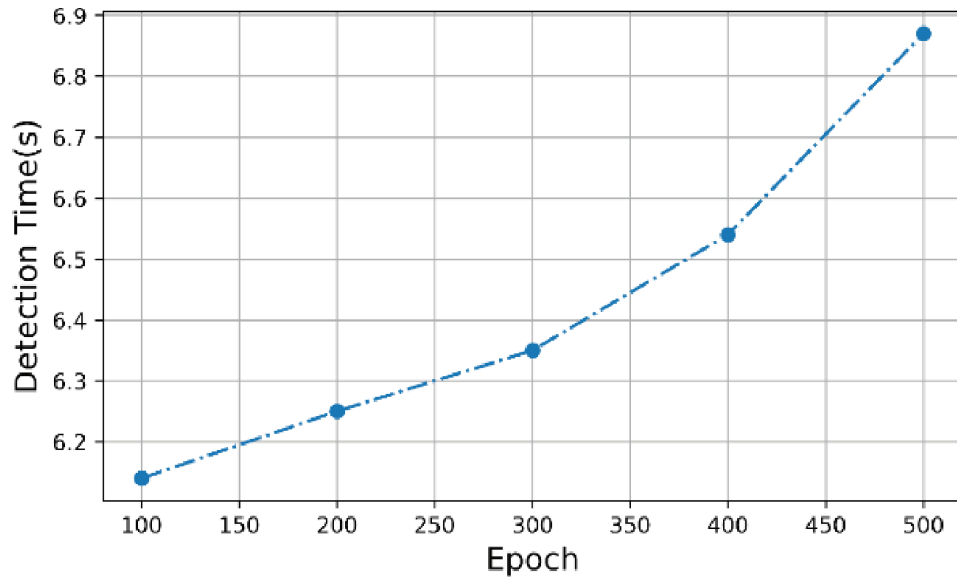


Figure 10: Performance of detection time in the proposed system.

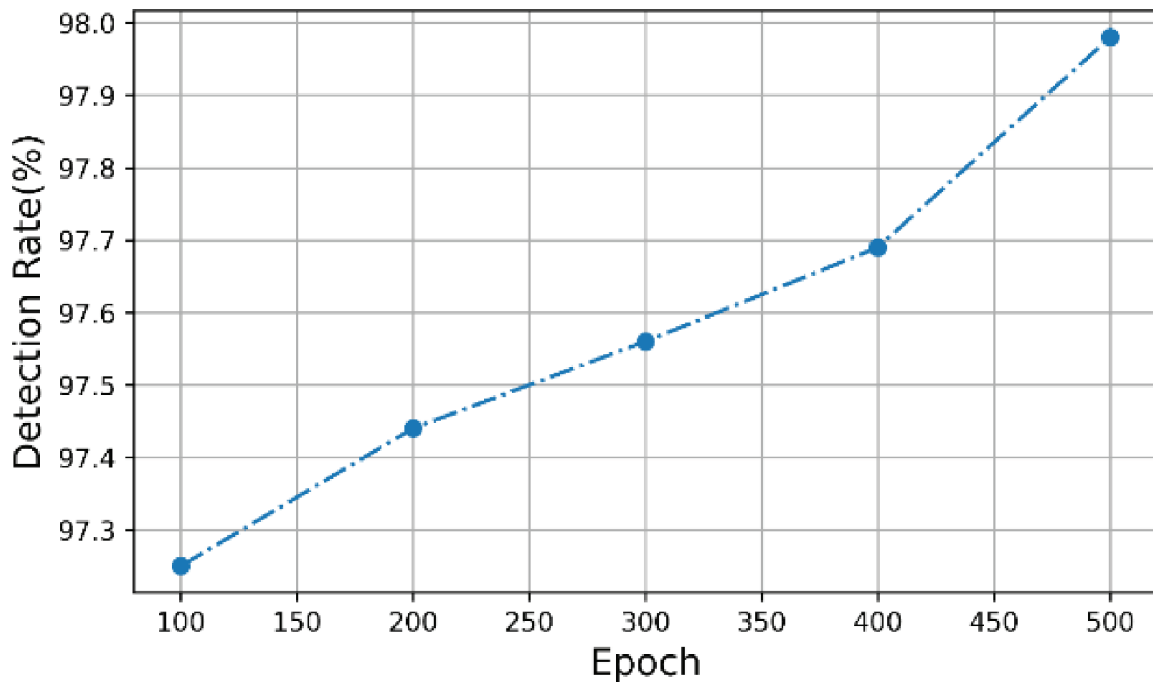


Figure 11: Performance of detection rate in the proposed system.

attains the value of 88.46%–95%. Moreover, when the epoch level is high, the recall value attains the maximum value. Symmetric CNN-GPOR is designed to effectively capture complex patterns and relationships in data, especially through its CNN-based

feature extraction, which enhances its ability to detect relevant positive instances in datasets. The polynomial regression component further fine-tunes the model to improve recall by reducing the chances of false negatives.

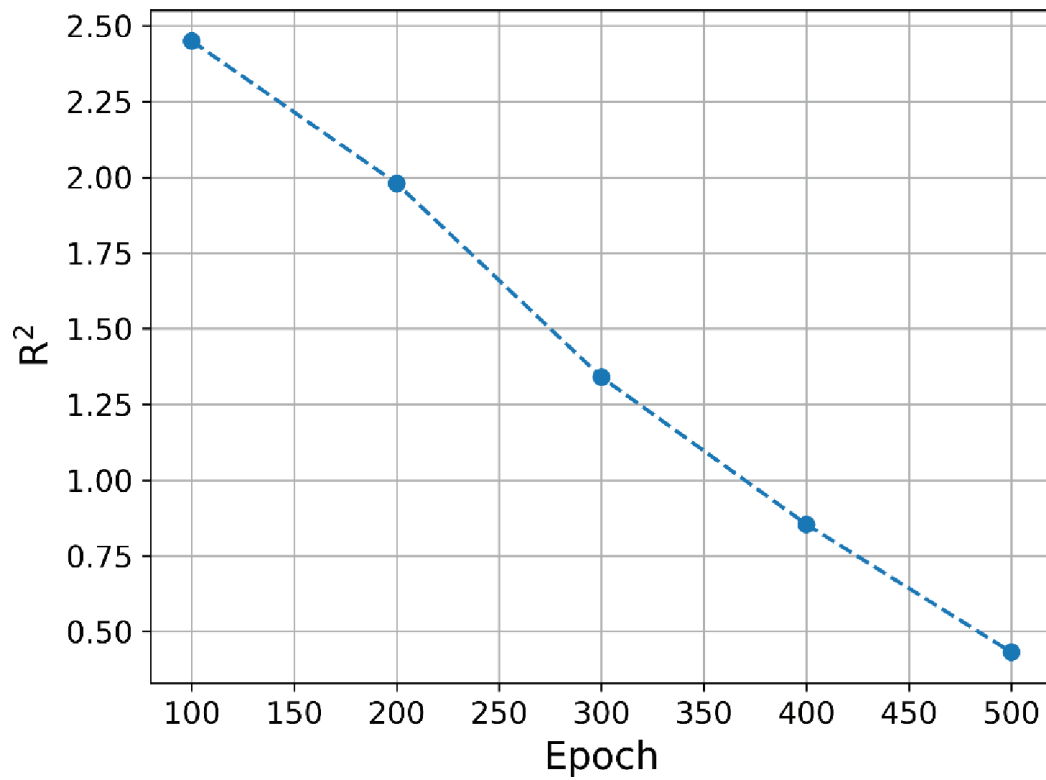


Figure 12: Performance R^2 in the proposed model.

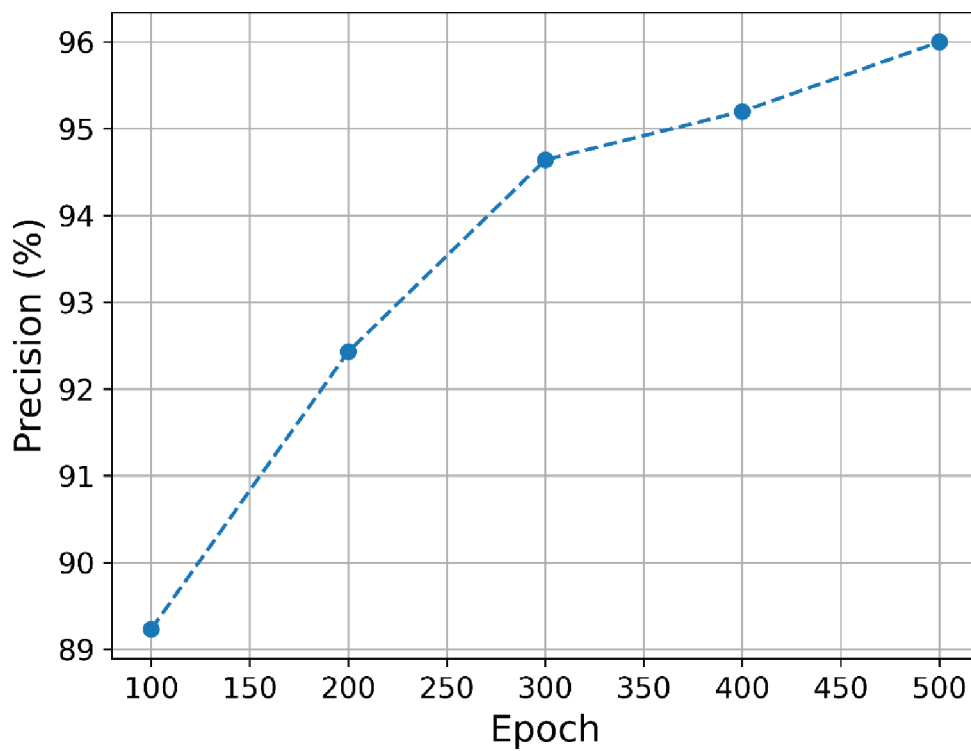


Figure 13: Performance of precision in the proposed model.

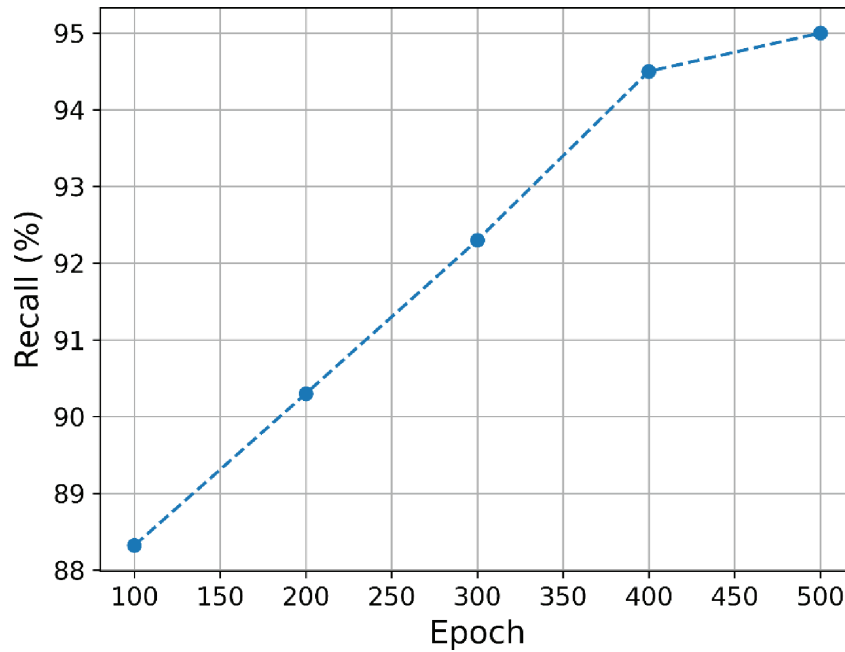


Figure 14: Performance of recall in the proposed model.

Overall, the experimental results of the proposed BQN-based decision support system and HSCNN-GPOR demonstrate significant improvements in PA. Key metrics, including MAE, RMSE, accuracy, loss, detection time, and detection rate, show substantial enhancements as epoch levels increased, with accuracy reaching up to 98.17% and detection rates improving to 97.98%. The system effectively predicts crop diseases and classifies pests with minimal error, offering high efficiency in real-time applications. These results underline the system's potential to optimize decision-making in farming, enabling targeted interventions and promoting sustainable, precision-driven agricultural practices.

c. Comparison of the proposed model with previous models

This section highlights the proposed BQN-based decision support system and HSCNN-GPOR for effective decision-making and to predict the futuristic disease and classifies the pests in crop performance by comparing it to the outcomes of existing approaches such as MLR [25], ANN [25], DT [26], RF [26], and showing their results based on various comparisons.

Figure 15 illustrates the MAE comparison between the proposed method and other existing techniques. The proposed method achieves an MAE of 9%,

outperforming MLR, ANN, DT, and RF, which record MAE values of 56%, 30%, 10%, and 10%, respectively. The error bars highlight the variability in performance, with the proposed method showing an error value of 0.57, compared to 2.50 for MLR, 1.43 for ANN, and 1.07 for both DT and RF. These results indicate that the proposed system performs 48% better than MLR, demonstrating its superior accuracy and reliability.

Figure 16 presents a comparison of the RMSE between the proposed method and other existing techniques. The proposed method achieves an RMSE of 9.2%, significantly outperforming MLR, ANN, DT, and RF, which show RMSE values of 72%, 50%, 36%, and 30%, respectively. The error bars indicate the performance variability, with the proposed method exhibiting an error value of 0.72, compared to 3.00 for MLR, 2.15 for ANN, 1.79 for DT, and 1.43 for RF. These results highlight that the proposed system delivers a 9.2% improvement over the existing MLR technique, demonstrating its superior accuracy and consistency.

Figure 17 illustrates the accuracy comparison between the proposed method and other existing techniques. The proposed model outperforms all other methods, achieving an impressive accuracy of 98.17%. In comparison, MLR, ANN, DT, and RF attain accuracy values of 38%, 22%, 34%, and 88%, respectively. The error bars highlight the variability in

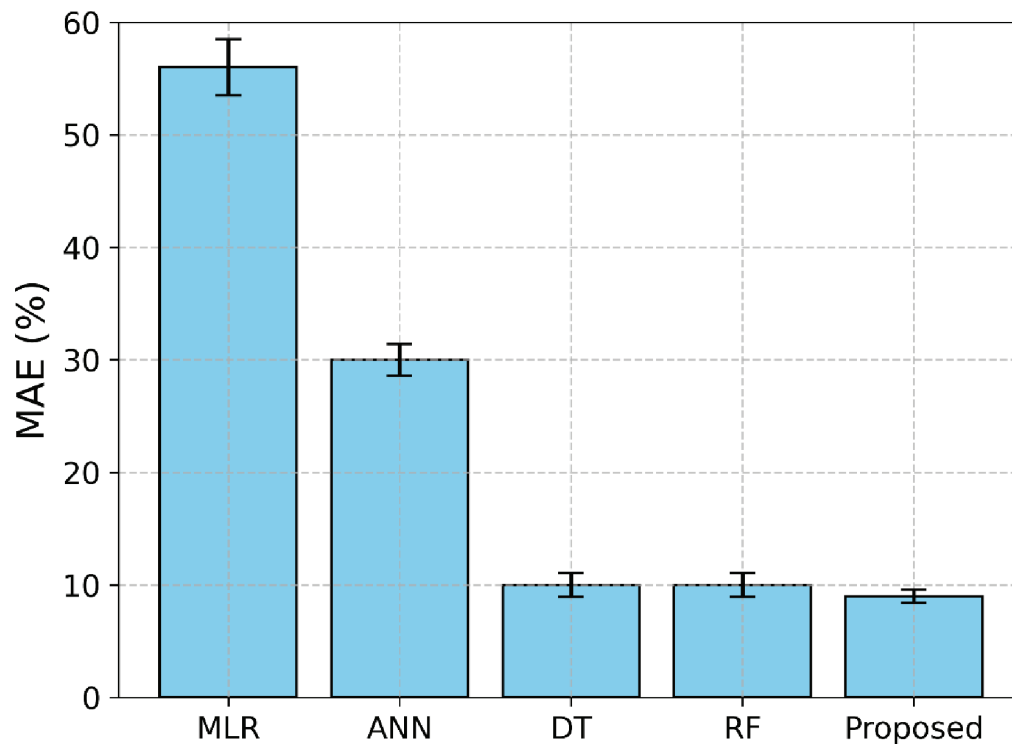


Figure 15: Comparison of MAE. MAE, mean absolute error.

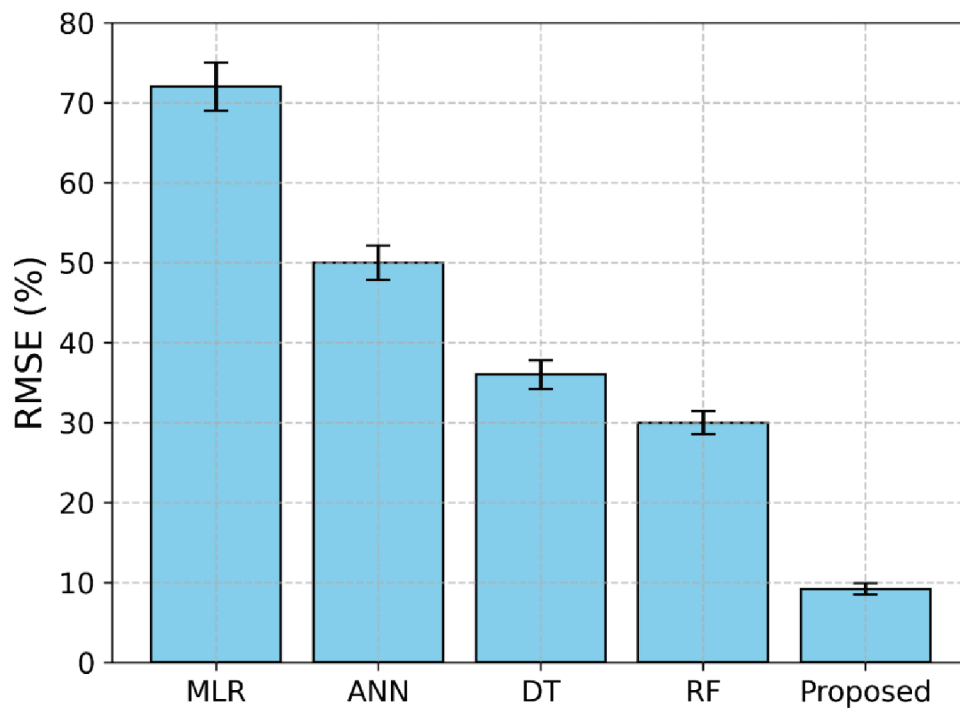


Figure 16: Comparison of RMSE. RMSE, root mean square error.

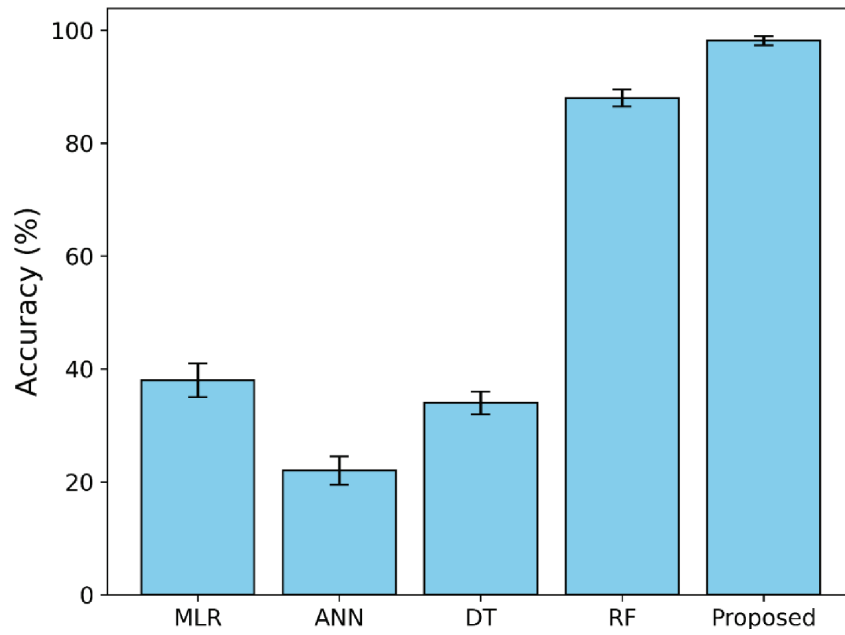


Figure 17: Comparison of accuracy.

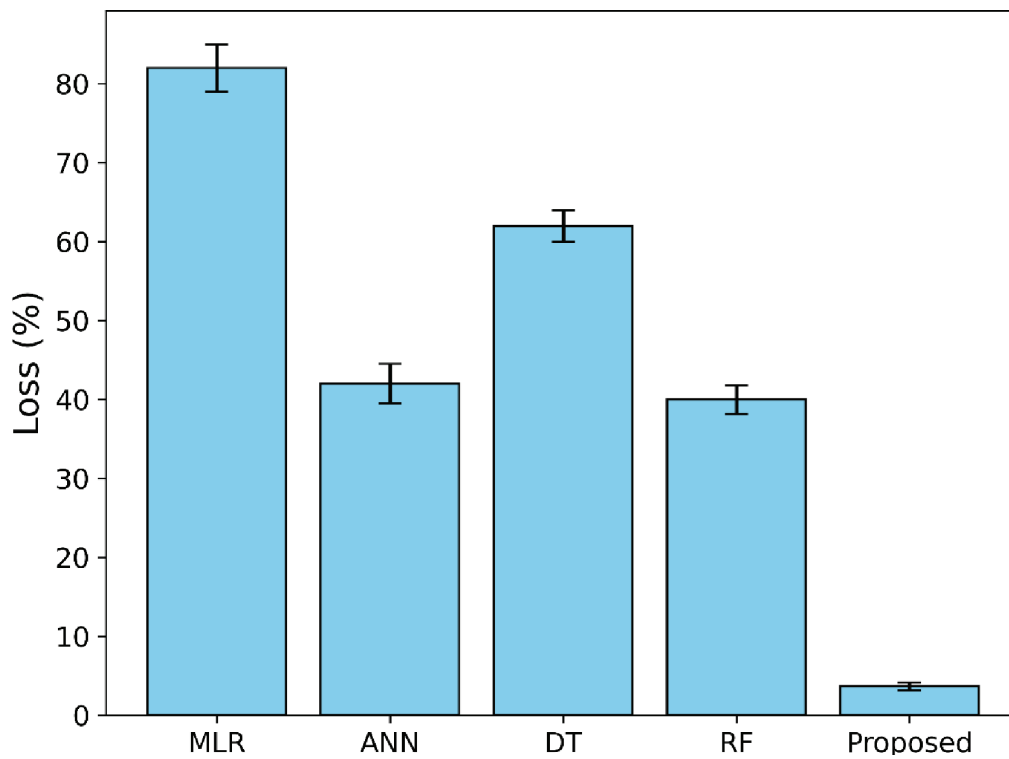


Figure 18: Comparison of loss.

performance, with the proposed method showing an error value of 0.8, while MLR, ANN, DT, and RF have error values of 3, 2.5, 2, and 1.5, respectively.

These results demonstrate that the proposed system is significantly more accurate than the existing techniques.

Figure 18 illustrates the loss comparison between the proposed method and other existing techniques. The proposed method achieves a loss of just 3.65%, significantly lower than MLR of 82%, ANN of 42%, DT of 62%, and RF of 40%. The error bars represent the variability in performance, with the proposed method exhibiting an error value of 0.5. In contrast, MLR, ANN, DT, and RF show error values of 3, 2.5, 2, and 1.8, respectively. This demonstrates that the proposed system has an 80% lower loss percentage compared to the existing techniques, highlighting its superior performance.

Figure 19 represents the detection time of the proposed method compared with other methods. Moreover, comparing the detection time with other methods such as MLR, ANN, DT, and RF attains 88%, 55%, 42%, and 55% respectively, and the proposed method achieves 6.89% detection time. The error bars highlight the variability in performance, with the proposed method showing an error value of 0.8, while MLR, ANN, DT, and RF exhibit error values of 4, 3, 2.5, and 2, respectively. This indicates that the proposed system outperforms existing techniques, achieving a detection time that is 80% lower than that of MLR, ANN, DT, and RF.

Figure 20 represents the detection rate of the proposed method compared with other methods.

Moreover, comparing the detection rate with other methods, such as MLR, ANN, DT, and RF attains 55%, 62%, 89%, and 36% respectively, and the proposed method achieves 97.98% of the detection rate. The error bars represent the variability in performance, with the proposed method showing an error value of 1.5, while MLR, ANN, DT, and RF exhibit error values of 3, 2.5, 2, and 2.5, respectively. This demonstrates that the proposed system achieves a detection rate that is 98% more accurate than the existing methods, highlighting its superior performance.

Overall, the proposed model shows that it is more efficient and more accurate when compared to previous models such as MLR, ANN, DT, and RF. The proposed system achieves more accuracy of 98.17%, when compared to other existing techniques, its detection time is 6.89%, which is higher than the existing techniques, and its loss percentage is 3.65% higher than the existing techniques. This proves that the proposed system performed well when compared to other existing techniques like MLR, ANN, DT, and RF.

V. Conclusion

To predict the futuristic disease in plants and to classify the pests, a novel BQN-based Decision Support

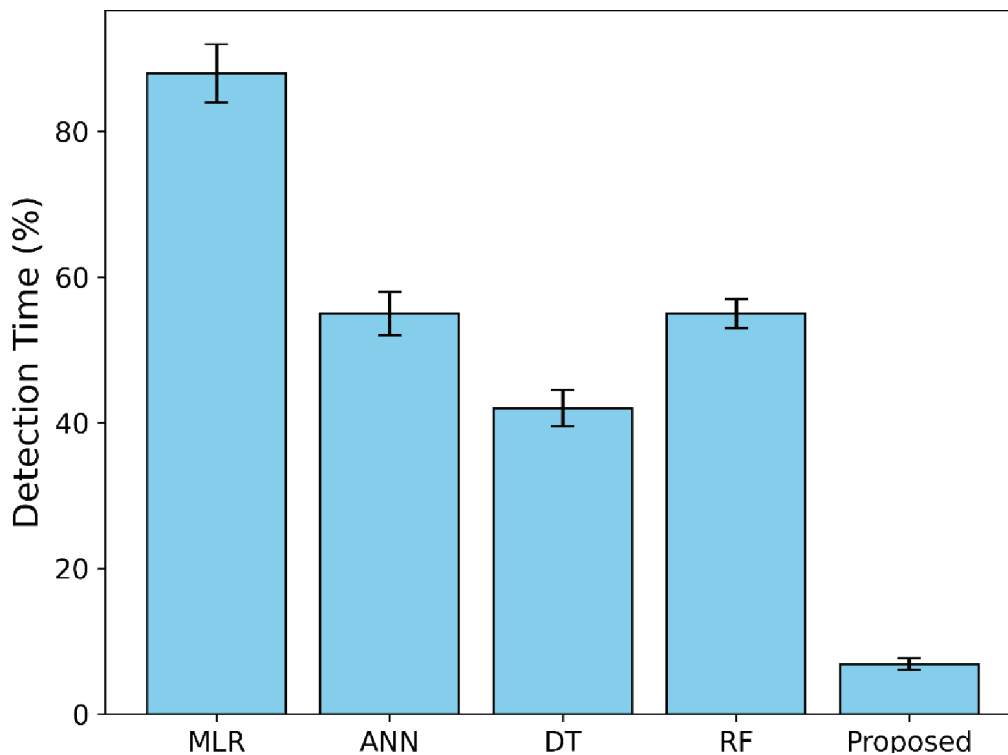


Figure 19: Comparison of detection time.

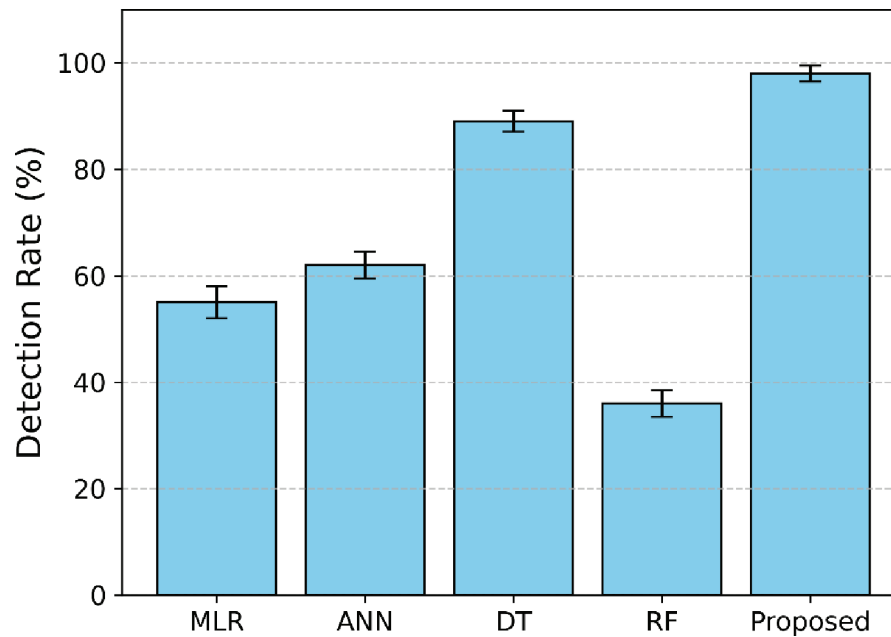


Figure 20: Comparison of detection rate.

System and HSCNN-GPOR have been proposed to resolve the difficulties where it currently predicts crop diseases. By using the fuzzy logistic associative rule, which effectively obtains the appropriate parameters of soil fertility and environmental elements without any loss, the decisive logistic associative rule-based BQN reduces the MAE to 9.0% and also reduces the RMSE to 9.2%, R^2 of 0.45. Symmetric CNN-GPOR enhances models precision of 96%, and recall of 95% and facilitates massive embedded decision-making through parallelized lattice distribution without any loss. The proposed model attains a high accuracy of 98.17% when compared to existing technologies such as MLR, ANN, DT, and RF and its detection time is 80% higher than the existing technique. The loss percentage is very low, which achieves a value of 3.65%, then it is more efficient to extract the features from the crop image by using GPOR which predicts the futuristic disease and classifies the pests in crops. When the proposed system is compared to any other of the existing techniques, MAE and RMSE are gradually decreased, the accuracy is gradually increased, and the proposed model's loss, detection time 6.89%, and detection rate achieve the rate of 97.98%, hence the proposed model performs well. Thus, the proposed system has been used to provide irrigation control, predict future disease in crops, and also classify the pests in crops, according to the results. However, in the future, it might be possible to use novel techniques

to detect and treat plant diseases. Future studies integrate deep learning and computer vision for real-time disease and pest detection, enhancing system adaptability through continuous learning. The use of IoT sensors and drones for real-time data collection provides richer datasets for more accurate predictions and responsive decision-making. Incorporating climate change models helps predict how environmental changes impact crop health and pests, supporting sustainable agriculture. Overcoming challenges like data scarcity and sensor calibration will improve system applicability across diverse regions and crops. This study paves the way for a more automated, data-driven approach to crop management, improving yields and sustainability.

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