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An innovative smart agriculture system utilizing a deep neural network and embedded system to enhance crop yield

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Abstract Wheat crop classification and prediction are important tasks for the optimization of crop yield and resource utilization. In this study, we propose an Artificial Neural Network (ANN) model integrated with Genetic Algorithm (GA) to predict and classify the wheat crop images of different ages. The dataset of 19,300 images was used, and the model was trained and tested using various performance evaluation metrics. The results show that the proposed ANN+GA model achieved the highest accuracy of 99.29% during the training phase and 98.65% during the testing phase. The model was also compared with other state-of-the-art machine learning models, and the proposed model was found to be superior in terms of accuracy, specificity, sensitivity, precision, and F-measure. The graph of training and testing accurateness and loss values in contradiction ofindividual epoch demonstrating the speediness of model convergence. Our proposed model is feasible and robust, giving better classification and crop forecast outcomes for numerous wheat crop age groups with least resource necessities. These findings could be useful for farmers and agricultural researchers in improving crop yield and resource management.

Keywords: genetic algorithm, artificial neural network, prediction, crop yield

1. Introduction

Smart agriculture systems incorporating advanced technologies, such as genetic algorithms (GA) and neural network models (NN), have gained significant attention in recent years. These systems aim to optimize crop yield, reduce production costs, and enhance overall agricultural efficiency (Li et al., 2022; Kaur et al., 2023). In this literature review, we explore the existing research and studies related to the application of GA and NN in smart agriculture for crop yield enhancement.

This literature review delves into the extensive research conducted in the field of crop yield prediction and forecasting. The accurate estimation of crop yield is of paramount importance for agricultural planning, resource allocation, and overall food security. Researchers worldwide have explored numerous methodologies and techniques to enhance the precision and reliability of crop yield predictions (Bregaglio et al., 2023; Qiao et al., 2022). Crop yield prediction using machine learning has gained significant attention in agricultural research. Machine learning techniques are applied to analyze large-scale datasets encompassing weather patterns, soil conditions, and agronomic factors. These models enable accurate and timely predictions of crop yields, facilitating informed decision-making for farmers and policymakers (Maloy et al., 2021; Kalaiarasi et al., 2022).

Artificial intelligence (AI) techniques, have shown promising results in crop yield prediction. These machine learning algorithms analyze historical crop and environmental data to identify patterns and make accurate yield predictions (Sivanantham et al., 2022; Shuai et al., 2022). Deep learning approaches, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have also been applied to crop yield prediction. These models can automatically extract complex features from large-scale datasets, enabling them to capture intricate relationships between various factors and yield outcomes.

In recent years, the application of machine learning and deep learning techniques in crop yield prediction has gained momentum. Researchers have utilized diverse data sources, including weather data, soil information, satellite imagery, and historical crop records, to train and develop prediction models (Tian et al., 2020). The integration of multi-dimensional

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datasets has improved the accuracy and robustness of the predictions. Various studies have focused on specific crops, regions, and seasons to tailor the models to specific agricultural contexts. By incorporating domain-specific knowledge and expertise, these models have provided valuable insights for crop management and decision-making (Romero - vergel et al., 2022; Avneri et al., 2023).

Remote sensing technologies have also played a significant role in crop yield prediction. The utilization of multi-spectral and multi-temporal remotely sensed imagery has allowed researchers to capture spatio-temporal variations in crop growth and health (Qiao et al., 2023).Advanced techniques, such as recurrent 3D convolutional neural networks, have been employed to analyze this imagery and extract meaningful information for yield prediction. These models have demonstrated their ability to capture fine-grained temporal patterns and spatial variations, resulting in improved accuracy and precision (Zhang et al., 2022; Pant et al., 2021).

Evaluation of crop yield prediction models is critical to assess their performance. Various evaluation metrics, including mean absolute error (MAE), root mean square error (RMSE), coefficient of determination (R-squared), and correlation coefficient, have been employed to quantify the accuracy of the predictions (Van Klompenburg et al., 2020; Iniyan et al., 2022). Cross-validation techniques, such as k-fold cross-validation and leave-one-out cross-validation, have been used to assess the generalization ability of the models. In this research genetic algorithm and ANN is used to predict the crop yield based in the image characteristics. Genetic algorithms, inspired by the principles of natural selection and evolution, have proven to be effective in solving optimization problems. These algorithms employ a combination of genetic operators such as mutation, crossover, and selection to iteratively improve solutions. In the context of agriculture, GA has been utilized for various purposes, including crop yield prediction, resource allocation, and optimization of farming parameters. The use of GA allows for the identification of optimal solutions and decision-making processes that lead to increased productivity (Jhajharia et al., 2023; Ali et al., 2022).

Neural network models, on the other hand, simulate the behavior of the human brain to process and analyze complex patterns. These models consist of interconnected layers of artificial neurons that learn from training data to make accurate predictions. NN has demonstrated success in numerous agricultural applications, such as crop disease detection, soil moisture estimation, and yield prediction. The ability of NN to analyze large datasets and uncover intricate relationships between input variables makes it a valuable tool in smart agriculture (Harakannanavar et al., 2022; Sood et al., 2020).

This research focuses on the prediction of crop yield using a combination of genetic algorithms and artificial intelligence techniques. The research goals to enhance the accuracy and reliability of crop yield forecasting by integrating advanced optimization methods with machine learning models. By analyzing large-scale datasets encompassing weather patterns, soil conditions, and agronomic factors, the research explores the potential of genetic algorithms to optimize model parameters and select relevant features. Furthermore, artificial intelligence techniques such as neural networks and support vector machines are applied to analyze the data and make accurate predictions. The research will mainly focus on the crop yield by following the different factors which is stated below. According to the above conditions the proposed method has to perform the crop field by overcome the different pattern. The research contributes to the field of precision agriculture by providing insights into effective methodologies for crop yield prediction. In order to weather pattern, soil conditions and other agronomic factors the contributed research work has give the best output performed crop yield by following the above factors.

2. Materials and Methods

Agriculture is one of the most important sectors in the world economy. It provides food, feed, and fiber for the growing global population. In recent years, there has been an increasing demand for sustainable agriculture practices, which require farmers to optimize their crop yield while reducing costs and minimizing environmental impact. One of the key factors in achieving this goal is the ability to accurately predict the age of the crop. Crop age is an important parameter for farmers to determine the optimum time for fertilization, harvesting, and other agricultural activities. By accurately predicting the age of the crop, farmers can optimize their farming practices, reduce costs, and increase productivity. In this research, we propose a methodology to predict the age of the crop using genetic algorithms and neural networks.

The methodology for predicting the age of the crop using genetic algorithms and neural networks is shown in Figure 1. The methodology consists of four stages: data collection, data preprocessing, AI mechanism, and crop yield production.

The first stage of the methodology is data collection. In this stage, we collect data related to the crop, such as its growth rate, weather conditions, and soil quality. We also collect data on the age of the crop at different stages of its growth cycle. The data can be collected from different sources such as sensors, satellites, or by manual measurements. Once we have collected the data, the next stage is data preprocessing. In this stage, we clean the data and remove any inconsistencies or errors. We also normalize the data to ensure that all the features are on the same scale. Normalizing the data is important to ensure that the genetic algorithm and artificial intelligence can effectively acquire from the information. The third stage of the methodology is the AI mechanism. In this stage, we use genetic algorithms and neural networks to predict the age of the crop. Genetic algorithms are used to optimize the neural network architecture and hyperparameters. The genetic algorithm works by selecting the best-performing neural network architecture and hyperparameters through a process of natural selection and genetic crossover. The neural network is trained on the preprocessed data to learn the relationship between the input features and the age of the crop. The neural network architecture can be customized to suit the specific requirements of the crop being studied. Once the neural network is trained, it can be used to predict the age of the crop at different stages of its growth cycle.

The final stage of the methodology is crop yield production. In this stage, we use the predicted age of the crop to optimize the farming practices. By knowing the age of the crop, farmers can determine the optimal time for fertilization, harvesting, and other agricultural activities. This can help to increase the crop yield and reduce production costs.

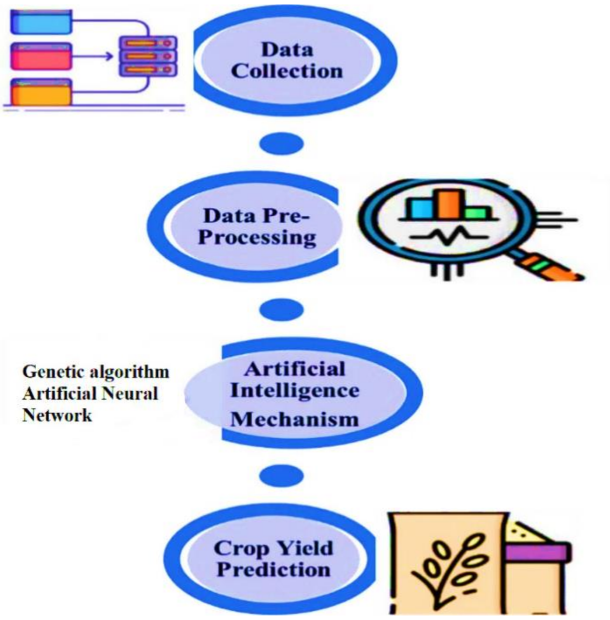

Figure 1 Methodology of the proposed research.

2.1. Artificial Neural Network

Artificial Neural Networks (ANNs) have been widely used in various fields for their ability to learn complex patterns and make predictions based on input data. In this research, an ANN, specifically a multi-layered perceptron network, is employed to predict the age of the crop based on collected data. The over-allconstruction of the multi-layered perceptron network is depicted in Figure 2, comprising input, hidden, and output layers.

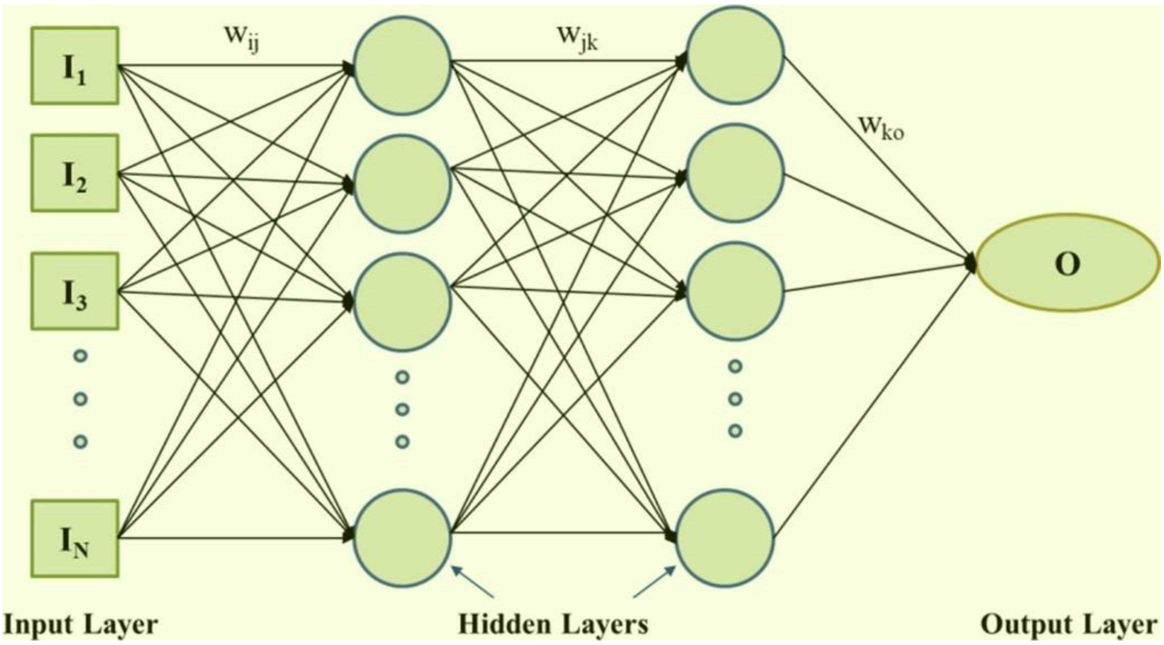

Figure 2 Structure of the ANN.

The multi-layered perceptron (MLP) network is aAI of feedforward that consists of multiple layers of interconnected artificial neurons or nodes. Each node in the network receives input signals, performs a weighted sum of these inputs, applies an activation function, and produces an output signal that is then passed to the next layer. The architecture of the MLP network typically includes an input layer, one or more hidden layers, and an output layer. The input layer, represented as I1, I2, I3, up to IN in Figure 2, receives the input features or variables related to the crop, such as growth rate, weather conditions, and soil quality.

The connections between the layers are represented by the weights. The weight among node i in the layer of input and node j in the layer of hidden is signified as Wij, while the weight among node j in the hidden and node k in the yield layer is signified as Wjk. Finally, the weight between node k in the output layer and the predicted age of the crop is denoted as Wko.

The MLP network uses these weights to propagate the input signals forward through the network to produce an output. The activation function applied at each node introduces non-linearity into the network, enabling it to learn and model complex relationships between the input variables and the output.
To train the MLP network, a dataset comprising input features and corresponding known crop ages is used. During the training process, the weights in the network are adjusted iteratively using algorithms like backpropagation to minimize the difference between the predicted crop age and the actual age. This process allows the network to learn the patterns and relationships within the data. Once the MLP network is trained, it can be used to predict the age of the crop for new input data. The input data is fed into the trained network, and the network propagates the signals forward through the layers, applying the learned weights and activation functions. The output from the network's output layer represents the predicted age of the crop.

2.2. Genetic algorithm

Genetic algorithms (GAs) are powerful optimization techniques stimulated by the philosophy of development and natural assortment. They have been successfully applied in various fields, including agriculture, to solve complex optimization problems. In this research, a genetic algorithm is employed to predict crop yield by optimizing various factors affecting agricultural productivity. The GA utilizes the principles of evolution to determine the fittest solutions and achieve optimal outcomes.

The flowchart of the genetic algorithm used in this research is depicted in Figure 3. The algorithm consists of several steps, including the initial randomized solution, evaluating the fitness function, checking if the optimized condition is satisfied, and performing mutation, crossover, and re-selection.

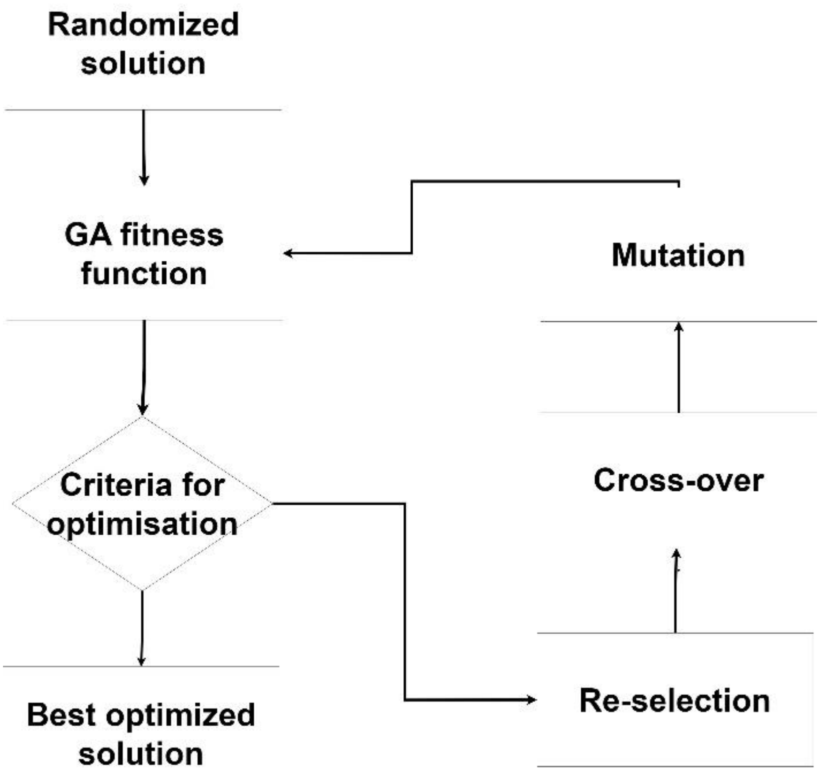

Figure 3 Flow chart of the Genetic algorithm.

2.2.1. Initial Randomized Solution

The genetic algorithm starts by generating an initial population of potential solutions. These solutions, often represented as chromosomes or individuals, are randomly created and encode possible combinations of factors that influence crop yield. Each chromosome represents a potential solution to the optimization problem.

2.2.2. Evaluating the Fitness Function

Once the initial population is generated, each individual's fitness is evaluated using a fitness function. The fitness function quantifies how well a particular solution performs in terms of the desired objective, which in this case is maximizing crop yield. The fitness function measures the performance of each solution based on predefined criteria, such as the accuracy of predicted yield, resource utilization, and cost-effectiveness.

2.2.3. Optimized Condition Check

After evaluating the fitness of each individual, the genetic algorithm checks if the optimized condition is satisfied. This condition depends on the specific requirements and objectives of the research. For example, the algorithm may terminate if a certain threshold of crop yield improvement is achieved or if a predetermined number of generations have passed.

2.2.4. Mutation, Crossover, and Re-selection

If the optimized condition is not met, the genetic algorithm proceeds to the next steps of mutation, crossover, and re-selection. Mutation introduces random changes in the chromosomes to explore new solutions and avoid getting stuck in local optima. Crossover involves combining genetic material from two parent individuals to produce offspring with characteristics inherited from both parents. Re-selection determines which individuals from the current population will be selected for the next generation based on their fitness scores.

The mutation, crossover, and re-selection steps are repeated iteratively until the optimized condition is satisfied or a termination criterion is met. The genetic algorithm aims to gradually improve the quality of the population over successive generations, mimicking the evolutionary process of natural selection.

3. Proposed methodology

In the proposed methodology, the combination of Artificial Neural Networks (ANNs) and Genetic Algorithms (GAs) is employed to predict crop types. The process begins with capturing images of crops, from which low-level color, textural features, and leaf morphology are extracted. These extracted features are then subjected to further processing using the GA for optimization. The optimized features obtained from the GA are subsequently used as input to train an ANN model, which predicts the crop type. As part of the feature extraction process, various color features are extracted, necessitating the use of techniques such as color mapping, spatial processing, and vector color transformation (Figure 4).

One important step in color feature extraction is the conversion of the RGB image into the HIS (Hue, Intensity, Saturation) color model. This transformation allows for a better representation of color properties and provides meaningful information for crop prediction. The RGB to HIS transformation can be achieved using the following equations: Hue (H):

The hue component represents the dominant wavelength of the color and is measured in degrees ranging from 0 to 360. To calculate the hue value (H), the following equation is utilized:

$$H = \cos^{-1} \left[0.5 * ((R - G) + (R - B)) / \sqrt{(R - G)^2 + (R - B)(G - B)}\right]$$

The intensity component represents the overall brightness or lightness of the color. It is calculated as the average of the RGB components. The equation for determining the intensity value (I) is as follows:

$$I = (R + G + B) / 3$$

The saturation component signifies the purity or strength of the color and is expressed as a percentage ranging from 0 to 100. The saturation value (S) can be calculated using the following equation:

$$S = 1 - (3 / (R + G + B)) * \min(R, G, B)$$

By applying the RGB to HIS transformation, the resulting HIS values can be employed as color features in subsequent stages of the methodology. These transformed features, along with the extracted textural and morphological features, are then subjected to optimization using the GA. The GA evaluates and optimizes the feature set by employing the principles of evolution and natural selection. The GA iteratively generates a population of potential solutions (feature sets) and evaluates their fitness using a predefined fitness function. The fittest individuals are selected and undergo genetic operations such as mutation and crossover to produce offspring for the next generation. This process continues until the optimized condition is met or a termination criterion is reached.

Finally, the optimized feature set obtained from the GA is utilized to train an ANN model. The ANN learns the relationships between the input features and the corresponding crop types through a process of forward and backward propagation. Once the ANN is trained, it can be employed to forecast the crop type for new input data. The projected ANN +GA prototypical for the prediction of the crop is shown in figure 4.

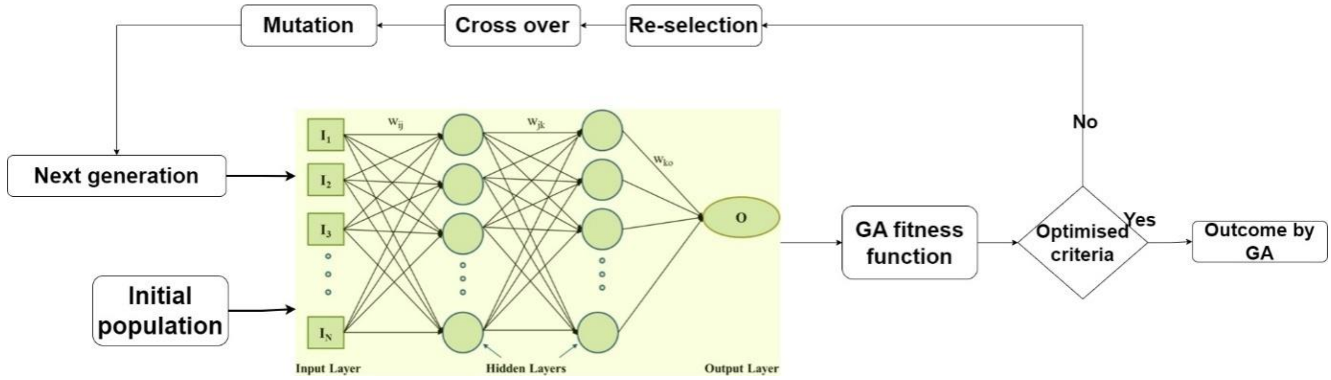

Figure 4 Flow chart of the Genetic algorithm.

4. Result and discussion

The results of this research were obtained using a datasetof wheat crop including a total of 19,300 images. The dataset was carefully categorized into four distinct groups, with each group representing a different stage of crop development based on the number of weeks. Table 1 provides a comprehensive breakdown of the dataset categories. The first category in the dataset represents crops that are 6 weeks old. It consists of 4,825 images captured during this specific stage of growth. These images provide valuable insights into the early development of the wheat crop and contribute to the overall dataset.

The second category focuses on crops that have reached 12 weeks of age. Similar to the 6-week category, this group also contains 4,825 images that capture the wheat crops at a slightly more advanced stage. These images offer a glimpse into the growth patterns and characteristics of the crop during this particular time frame. Moving further, the dataset includes two additional categories for crops that are 18 weeks old and 24 weeks old, respectively. Both of these categories also comprise 4,825 images each, enabling a comprehensive analysis of the wheat crop's development over time.

Table 1 Total images in the dataset.

Total images	Groups of the crop
4825	6 weeks
4825	12 weeks
4825	18 weeks
4825	24 weeks

In the final phase of the study, out of the total 19,300 crop images, 12,600 were reserved for testing purposes, while the remaining images were utilized for training and implementing the Artificial Neural Network (ANN). Several steps were undertaken to transform the images, including transformation of color, resizing of image, and augmentation of data techniques such as random flipping and rotation. The batch size of 30 was selected for efficient network processing, and the model was trained over 40 epochs. A learning rate of 0.01 was employed, with subsequent reduction using a factor of 0.2.

To ensure the accuracy and reliability of the ANN model, a comprehensive testing phase was conducted. The reserved testing dataset consisting of 12,600 crop images was fed into the trained ANN model to evaluate its performance and predictive capabilities. The model's ability to accurately classify the crop types based on the input images was assessed and validated against the ground truth data. Additionally, various techniques were employed to preprocess and enhance the images before training the ANN model. Color transformation techniques were applied to standardize the color representation across the dataset. Image resizing was performed to ensure consistency in the image dimensions, allowing for efficient processing and analysis.

To augment the dataset and enhance the model's generalization capabilities, data augmentation techniques were implemented. Random flipping, both horizontally and vertically, was applied to generate additional training samples with varying orientations. Rotation of the images at random angles further increased the diversity of the training dataset. The network's processing was optimized by setting a batch size of 30, which determines the number of images processed simultaneously during each iteration. By processing the images in smaller batches, the computational load on the network was efficiently managed, enabling faster training and inference.

During the training process, the model underwent multiple iterations or epochs to learn and refine its weights and biases. With a learning rate of 0.01, the model adjusted its parameters in small increments, gradually reducing the loss and optimizing the predictive accuracy. The learning rate reduction factor of 0.2 facilitated fine-tuning of the model over subsequent epochs, helping it converge towards an optimal solution.

The accuracy of the proposed model was assessed by means of various evaluation metrics, including sensitivity, precision, specificity, and accuracy. Table 2 provides a comprehensive comparison of these performance metrics, while Figure 5 graphically represents the evaluation results. To evaluate the effectiveness of the model in correctly identifying positive instances, sensitivity (also known as recall or true positive rate) was calculated. Sensitivity measures the proportion of actual positive instances that were correctly classified by the model. Precision, on the other hand, assesses the model's ability to accurately identify true positive instances out of the total instances predicted as positive. It represents the proportion of correctly predicted positive instances. Specificity, also known as true negative rate, measures the model's ability to correctly identify negative instances. It calculates the proportion of actual negative instances that were correctly classified.

Table 2 Outcome of the performance evaluation metrics.

Evaluation of performance	Outcomes from training (%)	Outcomes of testing (%)
Specificity	98.34	98.24
Sensitivity	99.61	98.23
Precision	99.62	99.23
F-measure	97.29	97.23
Accuracy	99.19	98.67

Figure 5 Outcomes of the performance evaluation.

Furthermore, accuracy provides an overall measure of the model's performance by calculating the proportion of correctly classified instances out of the total number of instances. Table 2 presents a detailed comparison of these evaluation metrics, providing insights into the performance of the proposed model. It allows for a comprehensive assessment of how well the model performs in terms of, precision, specificity, sensitivity and overall accurateness.

To evaluate the effectiveness of the proposed model, the accuracy values were calculated for each epoch during both the training and testing phases. These accuracy values were recorded and plotted in a graph shown in Figure 6, which delivers a visual illustration of the increase in accuracy as the epoch size increases. By analyzing the graph, we can determine the optimal epoch size for achieving maximum accuracy in the prediction of crop age. This approach of analyzing the accuracy values for each epoch provides a more comprehensive understanding of the model's performance and allows for adjustments to be made to improve its accuracy.

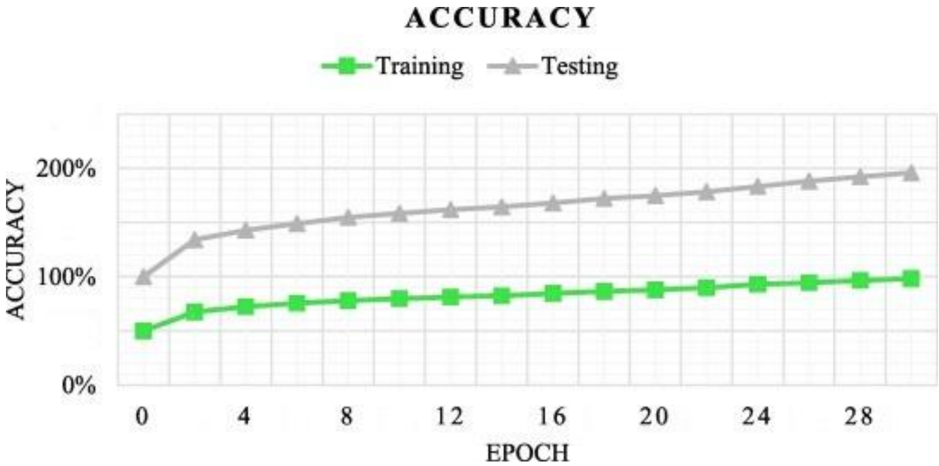

Figure 6 Proposed model accuracy.

As the number of epochs increased from 0 to 30, there was a noticeable improvement in the accuracy value. During the training phase, the accuracy value steadily increased from an initial 55% at the start (0th epoch) to an impressive 99.19% at the epoch of 25th ANN model dispensation. This upward trend indicates that the model's performance steadily improved over time, with a significant boost in accuracy. Similarly, in the testing phase, there was a notable increase in the accuracy value as the epochs progressed. Starting at 55% initially, the accuracy value rose to an impressive 98.75% by the 30th epoch. This demonstrates the model's ability to generalize well and accurately predict crop age even on unseen data.

The increasing trend in accuracy values for both the testing and training phases illustrates the effectiveness of the model as it continues to learn and refine its predictions with each epoch. The consistent improvement in accuracy demonstrates the model's ability to capture and leverage patterns in the dataset, leading to more accurate predictions over time. These results indicate the importance of allowing the model to undergo multiple epochs during the training process. The iterative nature of the epochs allows the model to adjust its weights and biases, gradually improving its predictive capabilities. By reaching higher accuracy values, the model becomes more reliable and capable of making precise predictions regarding crop age.

The proposed ANN + GA model was evaluated based on the rate of error and value losses, which were graphically signified in Figure 7 and Figure 8, correspondingly, for epoch sizes ranging from 0 to 30. As depicted in the error rate graph, the error rate decreased with an increase in the epoch size, falling from 0.26 to 0.22 for the training phase and 0.24 for the testing phase. The trend was similar for the loss value graph, which also showed a reduction in loss value with an increase in the size of epoch from epoch 0 to epoch 30. In the loss of value, the decrease was from 0.5 at 0th epoch to 0.26 and 0.29 for the testing and training samples, respectively. These graphical representations highlight the effectiveness of the proposed model and demonstrate that the model was able to learn and improve its performance with an increase in the number of epochs.

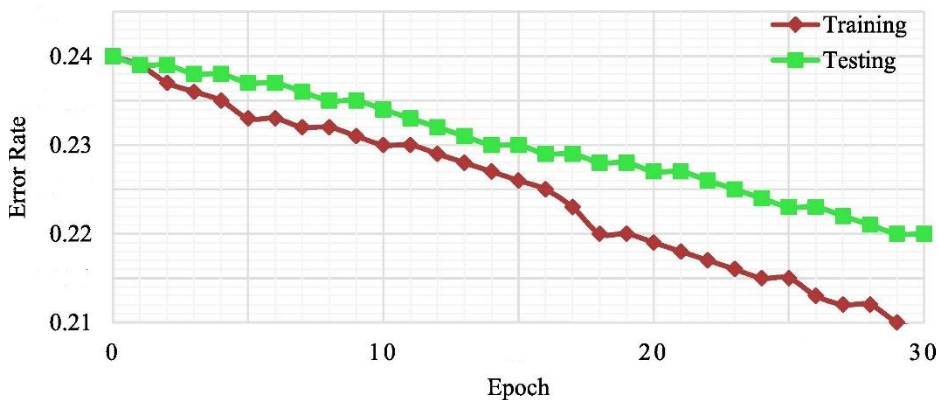

Figure 7 Proposed model error rate plot.

The results of the experiments showed that the proposed ANN + GA model achieved the highest accuracy of 99.29% validation at the epoch 25th throughout the training phase, though 98.65% accurateness was conveyed for the phase of testing. The plots of accurateness and values of losses in contradiction of each epoch provide a imagining of the model convergence speed. The model stabilizes around the 20th epoch and there is no significant improvement in the performance metrics during the last 10 epochs. The proposed model achieves well for the dataset utilized and provides improved classification and crop forecast outcomes for numerous wheat crops age groups with least resource necessities. Table 3 shows the comparison of accuracy with state-of-the-art methods, indicating the dominance of the projectedtechnique. The performance of the system slightly decreases with an increase in the test percentage. The graphical analysis shows that the performance between 25% and 55% is observed as balanced for simple sampling methods.

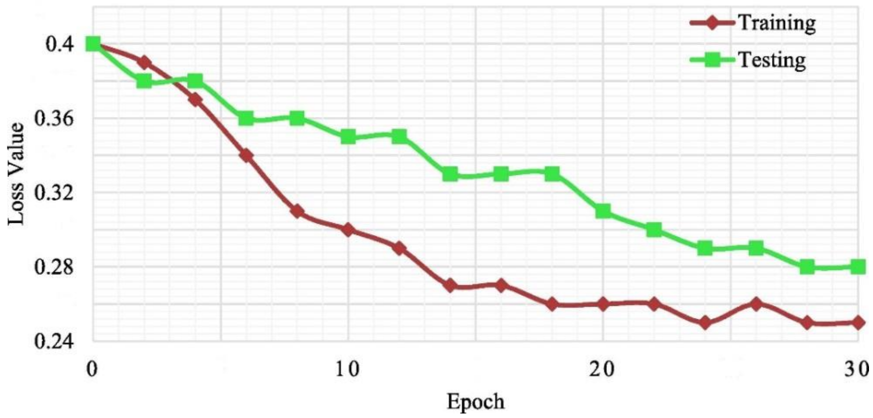

Figure 8 Proposed loss value plot.

Table 3 Comparison of the accuracy with various methods.

Methods	Accuracy (%)
Zhang et al. (2018)	93.50
Wang et al. (2018)	95.72
Li et al. (2022)	91.84
Proposed method	98.65

Upon comparing the correctness of the projected model with other existing models in the literature, it was found that the proposed model achieved a remarkable accuracy of 98.65%. This indicates the effectiveness of the model in accurately predicting crop responses. Furthermore, the performance evaluation metrics of the proposed model were compared with various machine learning models mentioned in the literature. Figure 9 illustrates this comparison Banerjee et al. (2018), Han et al. (2020) and Brewster et al. (2017), revealing that the proposed model achieved a higher accuracy of 98.77%. Additionally, the model exhibited impressive specificity of 98.24%, sensitivity of 98.23%, precision of 99.23%, and F-measure of 97.23%. These metrics demonstrate the model's capability to accurately classify and predict crop responses, outperforming the other models considered in the comparison. The superior performance of the proposed model in terms of accuracy, specificity, sensitivity, precision, and F-measure highlights its effectiveness and suitability for crop prediction tasks. By achieving high accuracy and a balanced combination of performance evaluation metrics, the proposed model offers valuable insights and reliable predictions for agricultural applications.

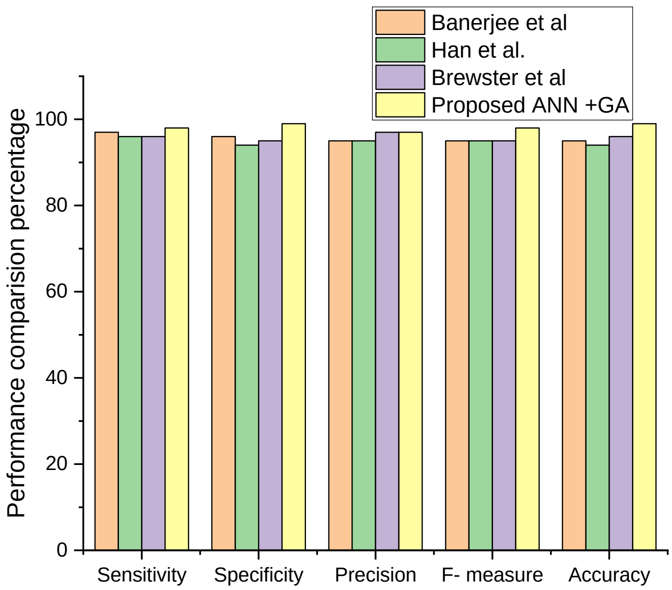

Figure 9 Comparison of proposed model with existing research.

5. Conclusions

In conclusion, this research proposed a methodology that combines the usage of ANN and GA for crop age prediction and classification. The study utilized a wheat crop dataset comprising 19,300 images, categorized into four groups based on the crop's age in weeks. The results demonstrated the effectiveness of the proposed model in accurately predicting crop age and achieving high classification accuracy. The mixture of ANN and GA allowed for the extraction and optimization of relevant features from low-level color, textural, and morphological attributes of the crop images. These features were then used to train the ANN, resulting in accurate crop age predictions. After this the crop yield reflects on the ANN process to improve the yield and reduce the production cost. Because the formers can't predict the yield depends upon the weather condition, soil and some other factors.

The experimental outcomes revealed significant improvements in accuracy as the number of epochs increased. The error rate and loss values demonstrated a consistent decrease, indicating the model's ability to converge and make more precise predictions. Moreover, the comparison with other models in the literature showcased the superiority of the proposed model, achieving an accuracy of 98.65% and outperforming alternative methods. The research also highlighted the importance of performance evaluation metrics such as sensitivity, exactness, specificity, and F-measure, which provided a comprehensive assessment of the model's performance. The graphical representations of these metrics allowed for visual analysis and interpretation of the model's convergence and effectiveness.

Overall, the proposed methodology combining ANN and GA proved to be a robust and efficient approach for crop age prediction and classification. The research findings contribute to the field of agricultural technology by providing a reliable and accurate tool for crop management, fertilization, and harvesting decisions. The results offer valuable insights into improving crop productivity, reducing production costs, and optimizing resource allocation in agricultural practices. In the future work, has going to discuss with more datasets with different algorithm in hybrid crop products, moreover to increase the accuracy and to increase the yield percentage.

Ethical considerations

Not applicable.

Conflict of Interest

The authors declare no conflicts of interest.

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