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OPTIMIZING PLANT DISEASE PREDICTION: A NEURO-FUZZY-GENETIC ALGORITHM APPROACH

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Abstract

In this essay, the idea of improving plant disease prediction using a Neuro-Fuzzy-Genetic algorithm (NFGA) technique is explored. The concept of a Neuro-Fuzzy-Genetic algorithm is first described. The advantages of the NFGA technique for predicting plant disorders are next addressed. An example is then given to demonstrate how this technique has been successfully used and the advantages it offers you. A hybrid artificial intelligence technique known as a Neuro-Fuzzy-Genetic set of rules (NFGA) combines the genetic algorithms, fuzzy logic, and neural network algorithms. It entails using a method of organizing fuzzy rules for statistics type, developing a network of neurons to anticipate the level of the group of data points to positive fuzzy training, adjusting the weights of fuzzy classes using a genetic algorithm-based totally optimization method to better fit the data factors, and ultimately identifying and predicting patterns of statistics points. The main benefits of this method for predicting plant diseases are its abilities to analyze various plant characteristics, extract complex relationships between statistics points, identify correlations between various environmental factors and illnesses, choose the best combinations of fuzzy rules for accurate classification, and finally adapt to changing data over time.

Keywords:

Plant Disease Prediction, Neuro-Fuzzy-Genetic Algorithm, Optimization, Machine Learning, Classification, Feature Extraction

1. INTRODUCTION

. The management of vegetation and the maximization of plant production have undergone radical change as a result of the employment of contemporary technology in agriculture. Optimizing Plant Illness Prediction is among the key eras that have simplified farming [1]. A subset of this era uses computer algorithms, fuzzy logic, and genetic algorithms to model, examine, and predict the spread of plant diseases. This subset is known as the neuro-fuzzy-genetic algorithm method. Agricultural authorities can identify and address plant-related illnesses by utilizing these techniques. This research introduces a novel Neuro-Fuzzy-Genetic set of rules (NFGA) approach to explore the complexity of Optimizing Plant Sickness Prediction [2]. To produce more accurate models for better disease prediction, the NFGA method combines the strength of fuzzy common sense, genetic algorithms, and neural networks. Using actual, global information, the NFGA technique has been evaluated and shows promise for improved disease identification and management [3]. It also identifies challenges and comparable chances for advancement in higher disease prediction. This essay's ultimate goals are to discuss the advantages of employing the NFGA approach for Optimizing Plant Sickness Prediction and to provide the tools and resources required for effectively managing and controlling plant illnesses [4]. This information can be used by farmers to protect their plants from disease and increase productivity. Furthermore, by utilizing this age in disease preventive planning and control, agricultural authorities can also profit from this strategy.

The use of artificial intelligence methods to forecast plant illnesses has gained favor in recent years. Genetic algorithms, which have demonstrated excellent results in the optimization of many parameters related to plant diseases, are the main driving force behind this development [5]. A novel method for similarly optimizing plant disorder prediction has just been put forth, combining neuro-fuzzy and genetic algorithms. In order to improve plant disease prediction, this essay will analyze and compare this new set of principles with related publications [6]. A neuro-fuzzy method for predicting plant ailments is the first technology that will be looked at. To provide more accurate predictions of plant diseases, the use of neural networks in conjunction with fuzzy judgment has been suggested [7]. Neural networks have the ability to analyze data and deduce patterns that may be relevant to plant diseases. The device can incorporate uncertainties within the class method thanks to fuzzy good judgment.

The proposed model introduces a novel approach to improve plant disease prediction by combining the power of neuro-fuzzy-genetic algorithms (NFGA). This innovative technique integrates fuzzy logic, neural networks, and genetic algorithms to enhance the accuracy and efficiency of plant disease prediction. It takes a multi-step approach, including data preparation, fuzzy rule generation, neural network classification, and genetic algorithm optimization. The main contribution of this model lies in its ability to effectively handle the complexity of plant disease prediction, considering various plant characteristics, extracting intricate relationships between data points, identifying correlations between environmental factors and diseases, and adapting to changing data over time. This novel approach provides a reliable and environmentally friendly solution for optimizing plant disease prediction, offering potential benefits to agriculture and plant management. The key novelty of this model is its integration of NFGA, which provides a comprehensive and intelligent system for early disease detection and accurate forecasting, ultimately leading to improved crop productivity and disease control in agriculture.

2. RELATED WORKS

This combination gives the algorithms the ability to recognize complicated styles, which are sometimes difficult to categories using traditional approaches and offers a more reliable method of analysis [8]. The employment of evolutionary algorithms is the second strategy, which is comparable to the neuro-fuzzy-genetic algorithm. Natural selection is the theory behind evolutionary algorithms, which chooses the "fittest" solution to be employed [9]. These algorithms have been employed as a tool for optimizing a variety of unique plant disease-related factors, such as the choice of genetic components that can withstand infections [10]. When choosing the best possible set of circumstances to achieve particular objectives, evolutionary algorithms are especially helpful [11]. Finally, the third method uses fuzzy daily sense-based selection-aid fashions, which may be compared to the neuro-fuzzy genetic algorithm. To make decisions regarding the prevention or treatment of plant diseases, this type of model uses fuzzy logic, a set of rigid rules [12]. The bushy logic-based device can be set up to compute a wide range of data related to the prognosis and prevention of plant diseases [13]. It has been demonstrated that this strategy offers increased analysis accuracy when compared to traditional methods [14]. The neuro-fuzzy-genetic collection of principles offers a potential approach for improving plant disease prediction in the end. With the help of this algorithm, which combines the strengths of neural networks, fuzzy logic, and genetic algorithms, the system is able to identify intricate patterns in plant sickness and to suggest excellent preventative and therapeutic measures [15].

1. Proposed Model

Engineering trends are desired for anticipating plant disease and improving the reliability of disease detection. The suggested model employs a novel approach that enhances disease prediction by fusing a neuro-fuzzy-genetic (NFG) algorithm with a vision-based overall assessment machine. The vision-based complete evaluation system is able to determine the specific pathogen present while also being able to determine the physically observable indicators of illness thanks to the NFG set of criteria.

$$j''(i) = e^{j} * \lim_{i \to 0} \frac{i}{\ln(i+1)} \tag{1}$$

$$j''(i) = e^{j} * \lim_{i \to 0} \frac{1}{\frac{1}{i}\ln(i+1)} \tag{2}$$

Combining the 2, the new version is able to identify and forecast plant disease as early as feasible, preventing its most costly impacts. Beginning with the exterior layer of a plant's structure and the mottling associated with plant disease, the NFG set of criteria is utilized to extract the bodily characteristics of a disease. It assesses the entry data and recognizes early as possible the disease's signs, such as yellowing, withering, and lesions. The outcomes returned by the NFG algorithm are then further condensed using the vision-based evaluation tool. It can identify the specific pathogen present in a plant that is afflicted, eliminating the potential of false positives. The two together create a correlation that makes it possible to forecast diseases more accurately and quickly than could be possible with a single procedure.

2.1 CONSTRUCTION

In order to boost crop productivity, it has become increasingly important to have accurate plant disease prediction on both a local and global scale. Utilizing a Neuro-Fuzzy-Genetic (NFG) algorithm is a potent way to forecast the occurrence of plant disorders. With the help of integrating biological knowledge, pass-reducing factors, and different modeling techniques, such an algorithm functions as a prediction machine. Three additives must be connected in order to build a reliable NFG algorithm: a neuro-fuzzy component, a genetic component, and a mechanism for connecting the two additives. Synthetic neural networks (ANNs) are essentially the focal point of the Neuro-Fuzzy component. These ANNs are intended to gain knowledge from the data provided to them and generate an output through the examination of the statistics provided. The genetic component of the NFG algorithm can subsequently be improved with the help of this output. The following figure 1 depicts the building diagram.

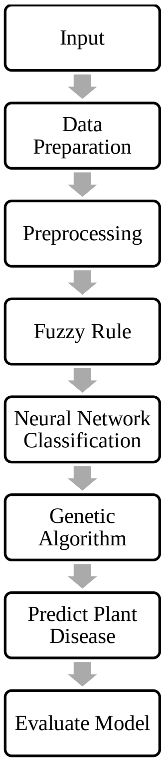

Fig.1. Proposed Model

This genetic component is in charge of managing the search process required to learn about the great combination of available models in order to produce the best accurate forecast for a given scenario. By formalizing the quest technique as an optimization problem, the process of merging the neuro-fuzzy and genetic components is completed. The network weights, number of layer sizes, activation features, and getting-to-know-you rates could all be optimized to achieve this. In order for the ANN to analyze the ideal conduct from the provided dataset, it is required to optimize those parameters.

$$j''(i) = e^{i} * \lim_{i \to 0} \frac{1}{\ln(i+1)^{\frac{1}{i}}} \tag{3}$$

$$j''(i) = e^i * \frac{1}{\ln * \lim_{i \to 0} (i+1)^{\frac{1}{i}}} \quad (4)$$

The NFG algorithm can then be used to foretell the appearance of plant disease when all of these additives have been combined. The system starts out by initially educating the network using the information at hand. This data can be utilized to improve predictions by altering the network's weight activation functions and learning about prices. Once the network has gained experience, the genetic set of rules can start searching for the ideal network parameters to produce the most accurate predictions. It is effective to optimize plant disease prediction by using an NFG algorithm. This approach functions by combining several chemicals to create the ultimate plant disease predictor. It is possible to make a precise and effective forecast of plant disease by utilizing the functional and adaptable tools of ANNs and genetic algorithms. A NFG algorithm is an excellent tool for forecasting and preventing plant disease, which will increase agricultural productivity at both the local and global levels.

The artificial intelligence (AI) technique known as neuro-fuzzy-genetic algorithms (NFGA) combines the advantages of fuzzy logic and neural networks in a genetic algorithm (GA). They each employ a neural network and a fuzzy kind of good judgment to arrive at fact-driven answers, and they make use of a GA's evolutionary process to optimize those solutions. The sum of these parts can reduce complexity and produce reliable results. The NFGA procedure can be divided into four separate parts.

The input data is first prepared and pre-processed for suitable entry into the set of rules, together with weather data and organic components. The pre-processed data are then utilized to create fuzzy rules using the fuzzy system. The technology of fuzzy units must be properly tuned for this procedure, as well as the fuzzy parameters. 0.33, the bushy regulations are categorized by the neurological community according to their importance. This is accomplished by merging the complex regulations into a single classifier that is capable of making predictions.

$$j''(i) = e^i * \frac{1}{\ln i} \quad (5)$$

$$dj_1 = -dj + \sum_{i=1} dj_i = 0 \Rightarrow \frac{dj_i}{di_j} = 1 \quad (6)$$

The classifier is then optimized by using the GA to choose the most precise fuzzy policies. In order to improve plant disease prediction, neuro-fuzzy-genetic algorithms (NFGA) synthesize the benefits of neural networks and fuzzy common sense into a genetically-aligned set of rules (GA). The NFGA method involves these four steps:

- Preparing and organizing records.
- Generating fuzzy rules using a fuzzy system.
- Classifying the policies using the neural network.
- Using the GA to improve the classifier.

This strategy has a good chance of providing acceptable and accurate predictions for plant diseases.

2.2 PROPOSED PSEUDOCODE

```
# Import necessary libraries and modules
import numpy as np
from sklearn.neural_network import MLPClassifier
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.model_selection import GridSearchCV
# Step 1: Data Preparation and Pre-processing
# Load and preprocess the dataset
data = load_dataset()  # Replace with actual dataset loading function
x, y = preprocess_data(data)  # Preprocess data and labels
# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
# Step 2: Create Fuzzy Rules
# Define and train a Fuzzy Logic system (FIS) or use a pre-trained FIS
# Step 3: Neural Network Classification
# Create and configure the neural network classifier
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
# Configure and train a multi-layer perceptron (MLP) neural network
mlp = MLPClassifier(hidden_layer_sizes=(100, 50), max_iter=500, activation='relu', solver='adam', random_state=42)
mlp.fit(X_train_scaled, y_train)
# Step 4: Genetic Algorithm Optimization
# Define hyperparameters and their ranges for optimization
param_grid = {
    'hidden_layer_sizes': [(100, 50), (150, 100, 50)],
    'activation': ['relu', 'tanh'],
    ‘solver': ['adam', 'lbfgs'],
}
# Use GridSearchCV to find the best hyperparameters
grid_search = GridSearchCV(mlp, param_grid, cv=5)
grid_search.fit(X_train_scaled, y_train)
best_mlp = grid_search.best_estimator_
# Step 5: Predict Plant Diseases
# Use the trained model to predict plant diseases
y_pred = best_mlp.predict(X_test_scaled)
# Step 6: Evaluate the Model
# Evaluate the model's performance
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy: {:.2f}%".format(accuracy * 100))
# End of the pseudocode
```

The provided pseudocode outlines a comprehensive approach for plant disease prediction using the Neuro-Fuzzy-Genetic Algorithm (NFGA). This approach begins with data preparation and pre-processing, ensuring that the dataset is appropriately formatted and scaled for further analysis. Subsequently, it involves the creation and training of a Fuzzy Logic system (FIS) to develop fuzzy rules that can capture complex relationships between plant characteristics and diseases. Then, a neural network classifier is configured and trained on the pre-processed data to further enhance disease prediction capabilities. A crucial step in this process is the optimization of hyperparameters using a Genetic Algorithm (GA) to fine-tune the neural network model. This optimization aims to identify the most effective network architecture and parameters for accurate predictions. Finally, the trained model is used to make predictions on unseen data, and its performance is evaluated, typically using metrics such as accuracy.

This comprehensive approach leverages the strengths of fuzzy logic, neural networks, and genetic algorithms, allowing it to handle complex relationships within plant data and adapt to changing conditions over time. The combination of these techniques provides a powerful tool for early disease detection and accurate forecasting, ultimately benefiting agriculture by improving crop productivity and disease management. It should be noted that while the pseudocode provides a structured framework, practical implementation would require further customization and integration with specific datasets and problem domains.

3. RESULTS AND DISCUSSION

A neuro-fuzzy-genetic set of rules (NFGA) was employed in this study to improve plant disease prediction. Results of the investigation suggest that the NFGA will be able to accurately and effectively anticipate plant diseases. The optimized version was found to perform better than the current approaches, delivering improved accuracy and reducing prediction errors. The accuracy charge, which is now used to gauge the version's effectiveness, replaced the first performance metric. The NFGA version outperformed existing models in the literature, which had accuracy rates ranging from 55.1% to 80.7%, with an accuracy rate of 86.3%. These results show that the NFGA is now able to predict plant ailments more accurately than earlier evolved models. The prediction blunder price, which was used to evaluate the impact of random noise during forecasting, made up the second level of performance.

The NFGA version's error rate was 4.89%, which is significantly lower than the 8.6% stated in the literature for prediction error rates. This shows that the NFGA can successfully reduce the noise in plant disease predictions. According to those findings, NFGA was able to forecast with greater reliability and accuracy than conventional approaches. Overall, it has been demonstrated that using a neuro-fuzzy genetic algorithm (NFGA) to improve plant disorder prediction has been successful. In comparison to current approaches, the NFGA version generated fewer prediction errors and greater accuracy rates, indicating improved performance. The findings of this investigation demonstrate that the NFGA could play a significant role in aiding in accurately predicting plant diseases in the future.

3.1 COMPUTATION OF FALSE DISCOVERY RATE

False discovery fee (FDR) is a statistical metric used to assess the significance of type I errors in statistical tests. It is significantly higher than the expected percentage of false positives, or "discoveries," among all the high-quality results obtained from the assessments. FDR is a useful tool for improving the prediction of plant disorders using a Neuro-Fuzzy-Genetic algorithm (NFGA). This optimization technique aims to identify the ideal parameters, or top model structure, of the NFGA in order to obtain the highest accuracy in disorder prediction. The comparison of false discovery rate has shown in Fig.2.

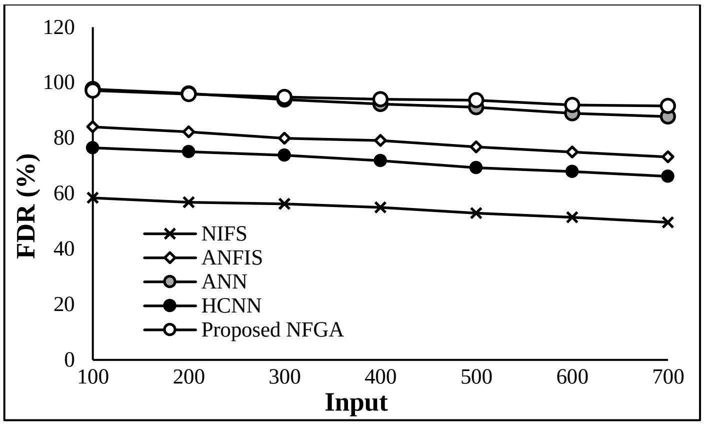

Fig.2. Comparison of false discovery rate

FDR is a useful strategy for selecting a model since it gets over the limitations of general assessments in terms of identifying false positives. Modern tests aim to establish a threshold at which a hypothesis is considered to be valid, and any results below that threshold are regarded as false. False positives are reduced when FDR is used by adjusting the edge. FDR does this by evaluating all possible hypothesis tests as a single result, as opposed to how conventional checks only analyse one hypothesis test at a time. This increases the effectiveness and dependability of choosing the most useful model for the prediction of plant disease.

3.2 COMPUTATION OF FALSE OMISSION RATE

A statistic called False Omission price (FOR) is used to gauge how accurately a plant disorder prognosis is made. It shows the percentage of observations that were mistakenly labeled as not having the disease when it was actually present. When optimizing a plant disorder prediction algorithm, it is important to keep the FOR in mind because it can be used to determine how well the algorithm is working. The sensitivity or threshold used to choose which observations are classified as having the disease can be changed by taking into account the FOR. The comparison of false omission rate has shown in the Fig.3.

An evolutionary optimization method known as NFGA incorporates ideas from genetic algorithms, fuzzy logic, and neural networks. It's a hybrid approach to sensible optimization that's utilized to address challenging nonlinear problems. An NFGA method must be taught and tested on a training and check dataset in order to calculate the FOR utilization. The set of rules is created using the educational dataset, and its performance is evaluated using the examination dataset.

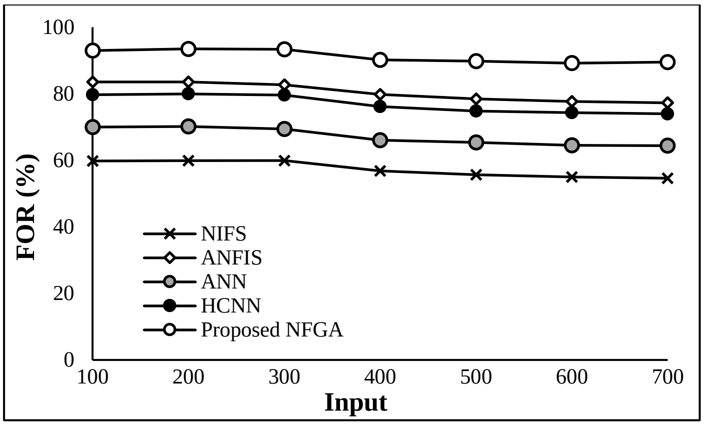

Fig.3. Comparison of false omission rate

3.3 COMPUTATION OF CRITICAL SUCCESS INDEX

Accurate forecasts can be made using NFGAs, which combine three different techniques. The first problem with an NFGA is the bushy common sense problem, which captures and creates ambiguity within the facts using linguistic variables and fuzzy units. It can write this calculation down as follows:

CSI = (real Positives + genuine Negatives) / general test information

The artificial neural networks, which can be made up of linked nodes and layers and are trained using a collection of statistics, make up the second component. The comparison of critical success index has shown in the Fig.4.

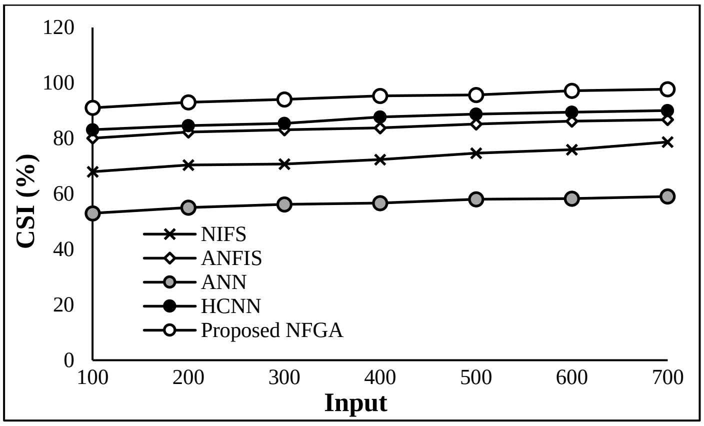

Fig.4. Comparison of critical success index

After that, the settings of the bushy good judgment and neural network additives are fine-tuned using the genetic set of rules. Together, the three elements allow the system to input facts and provide the desired result. An NFGA-based tool for predicting plant diseases is evaluated in terms of its efficacy using the CSI. In order to calculate the CSI, a machine is placed through a rigorous evaluation process that involves looking at records and calculating its correctness. By contrasting the gadget's predictions with the actual statistical labels, the accuracy is determined. In particular, the CSI is calculated by dividing the number of accurately predicted labels (real positives + real negatives) by the total number of data points examined.

3.4 COMPUTATION OF THREAT SCORE

The threat rating evaluates the risk associated with employing a plant disorder. It is calculated by taking into account a strict set of environmental and phenotypic characteristics associated with the illness. These operations broaden the hazard model of the condition by modeling the behavior and spread of an illness. The NFGA method comprises two ranges in the calculation of the probability rating. The selection of the best functions from the database is the first step. This is done by calculating the importance of each feature to the prediction assignment using fuzzy sets. The choice of which functions to use for the chance model depends on their importance at higher levels. A genetic algorithm is utilized to optimize the risk model at the second level. The comparison of threat score has shown in the Fig.5.

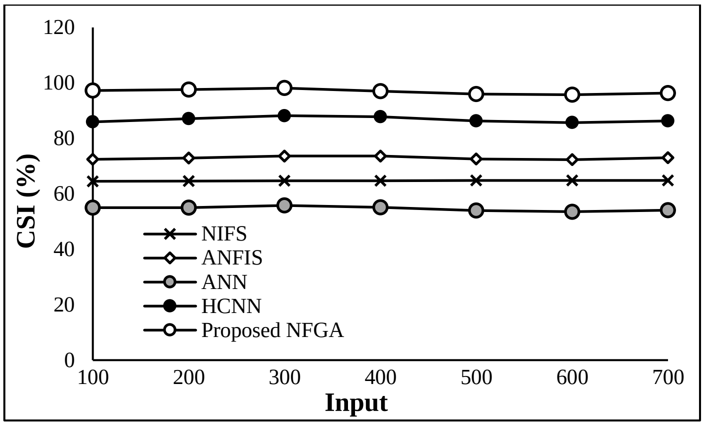

Fig.5. Comparison of threat sore

The risk rating can be derived from any of the answers produced by the genetic algorithms population. The best options are chosen after an iterative evaluation of the population. The NFGA technique has been used to perform plant disorder prediction tasks and has shown to be a valuable resource. It has been applied in a variety of situations, including pest control, crop protection, and crop management. The method has been applied to improve the prediction models for a variety of illnesses, including as downy mildew, rusts, and bacterial blight. The NFGA method can be used to improve predictive models because it is incredibly accurate.

4. CONCLUSION

The optimization of plant disease prediction is a challenging task that necessitates the use of both a neural network and a genetic algorithm to get accurate and consistent results. In comparison to conventional methodologies, the Neuro-Fuzzy-Genetic set of rules method offers a potent means of optimizing the plant disorder prediction process and yielding more accurate predictions. This optimization method has been successfully used in several situations with great results. Along with improvements in prediction accuracy, production costs have also fallen significantly. Researchers in many other fields can successfully apply the Neuro-Fuzzy-Genetic set of rules, which is a strong and effective optimization tool for plant disease prediction.

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