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Crop Recommendation System Based Soil & Environmental Factors Using Graph Convolution Neural Network: A Systematic Literature Review

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Abstract: Data-driven agricultural yield and resource management are becoming increasingly frequent in agriculture as technology progresses. Based on a broad variety of environmental variables, this research compares two graph-based crop recommendation algorithms, GCN and GNN. Our method selects the optimal crop for a season based on nitrogen, potassium, and phosphorus levels, temperature, humidity, soil pH, and rainfall. We assess the dataset's complexity using GCN and GNN, which handle graph-based structured data well. We utilize supervised learning to structure input information as nodes in a graph with edges reflecting plausible feature relationships to predict the optimum crop label given environmental conditions. Our experiment creates a graph via data preprocessing. Crop recommendation effectiveness is assessed using F1-score, recall, accuracy, and precision for both models. To prevent overfitting and ensure generalizability, we employ k-fold cross-validation. Our crop suggestion comparison of GCN vs. GNN shows their pros and cons. Due to its concentration on graph convolution and feature aggregation, GCN captures localized connections in the feature graph better than GNN, which competes in situations needing larger feature interactions. This research advances graph-based models in agriculture and their potential to enhance precision agriculture. We prioritise choosing the optimum graph-based model based on the dataset's nature and inherent links to optimize crop management and resource allocation.

Keywords: crop recommendation, graph-based models, environmental factors, comparative analysis

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1. Introduction

India is a country that is leading producers of agricultural goods. The agriculture industry employs 58 percent of the total Indian population as well as it contributes 17% of the country's GDP. Crop relies on a multitude of factors, including the type of soil, the amount of rainfall, the amount of sunlight, irrigation, fertilizer use, insect presence, and land preparation [1,2]. One of the most frequent challenges that Indian farmers must overcome is the fact that they do not choose their crops in accordance with the terrain and the climate [3]. Considering the fact that climatic conditions and the characteristics of the soil have a direct impact on crop yield, it is necessary to develop crop management practices that consider the appropriateness of the site and the soil [4]. Weather and agriculture are closely intertwined; therefore, it is essential to adapt to changing climatic trends in a productive way. Using climate-smart agricultural practises may help increase productivity and produce quality [5].

Precision agriculture has recently brought about significant advances in the world of agriculture, with an emphasis on irrigation systems, fertilizing, crop monitoring, and yield prediction [6]. Choosing the appropriate crop in relation to location-specific soil factors and climatic conditions is also vital for enhancing production [7]. Therefore, farmers must be equipped with instruments that allow them to choose the best crop for the region's unique meteorological and soil conditions [8]. In developing nations, using machine learning for agricultural planning objectives has resulted in the development of applications such as crop recommendation, crop disease diagnosis, fertilizer management, and so on [9]. The farmers would profit from the development of the crop recommendation system considering location-specific factors. The research described in this article tries to create a recommendation algorithm that offers greatest produce based on terrain and climate factors unique to a particular region [10]. In this paper, the graph Convolution neural networks model was utilized for the recommendation on crops system depending on terrain and environmental factors [11].

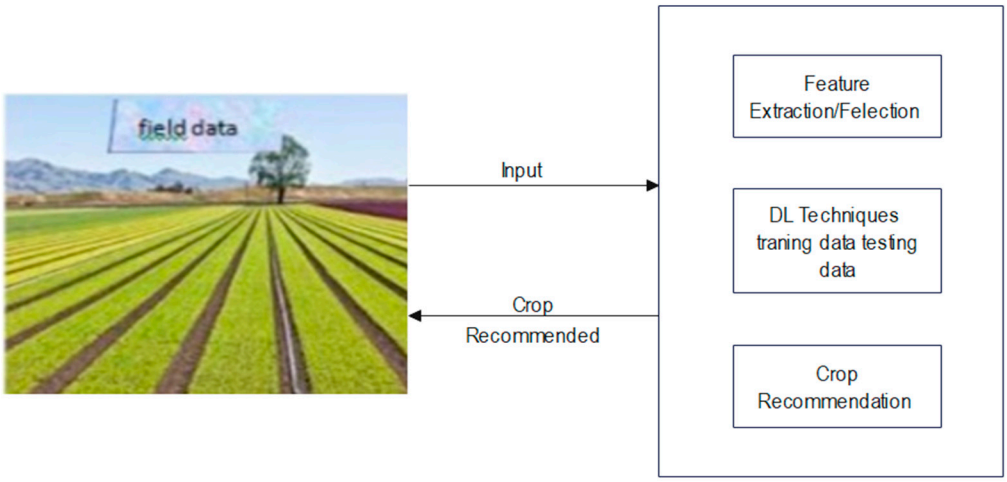


Figure 1. Crop Recommendation system using Deep Learning.

2. Background

In this section we discussed about the proposed model Graph Convolution Network (GCN) and existing model Graph Neural Network (GNN) along with their architectures.

2.1. Graph Convolution Network (GCN)

In recent years, graph-based neural networks, which generalize deep neural network models to graph data with structure, have gained popularity as well as link prediction (Ma et al., 2019).(Zhang et al., 2021) Let A be the adjacency matrix with a weighted undirected graph G, as well as the element A(i, j) in the matrix's ith row and jth column represents the weight of the edge (i, j). The definition of degree matrix D is as follows:

$$D(i,j)=\sum_{j=1}^{n} A(i,j) \tag{1}$$

The normalized symmetric the following definition applies to the graph G's Laplace matrix:

$$L=I-D^{-\frac{1}{2}}AD^{-\frac{1}{2}} \tag{2}$$

As a positive semidefinite real symmetry matrix, L may be divided into:

$$L=UAU^T \tag{3}$$

whereas $U=(u_0,u_1,...,u_{n-1})$ is the matrix of eigenvectors, and $\wedge=\begin{bmatrix}\lambda_1 & \dots & 0\\ \dots & \dots & \dots\\ 0 & \dots & \lambda_n\end{bmatrix}$ is the eigenvalues diagonal matrix. As the Fourier transform ecosystem on the graph, the normalized Laplacian matrix L & its eigenvector u creates an orthogonal space. The vector of features of each node in the graph represented by the graph signal is given as $x=(x_0,x_1,...,x_{n-1})\in R^n$. The graph signal x's Fourier transform is shown below.

$$\hat{x}=U^T x \tag{4}$$

Calculate the convolution of the two signals as follows:

$$x*g=U((U^T x)(U^T g)) \tag{5}$$

If $g_\theta=diag(U^T g)$ is used as a filter for a graph signal x, and the graph convolution may be defined as follows:

$$x*g_\theta=Ug_\theta(\wedge)U^T x \tag{6}$$

However, because of matrix-vector multiplication, the model's computational cost is $O(n^2)$, which is rather high. A K-degree polynomial filter is used in the convolutional layer of a model known as ChebNets to address this issue. The model's k-th polynomial filter for the spectrum is written as follows.

$$g_\theta=\sum_{k=0}^{K}\theta_k\lambda_1^k \tag{7}$$

In order to ensure spatial locality, the K-order polynomial filter of the spectrum is represented in the node domain as an aggregate of K-order neighborhoods, and the number of filter parameters is also kept to O(K) = O(1). The model utilizes Chebyshev polynomial $T_k(x)=2T_{k-1}(x)-T_{k-2}(x)$ to further minimize computing complexity, for recursive computation, where $T_0(x)=1 and T_1(x)=x$. As a result, the definition of the convolution of the filter and graph signal x is provided below.

$$x*g_\theta=U(\sum_{k=0}^{K}\theta_k T_k(L))U^T x \tag{8}$$

In order to achieve numerical stability, the matrix of adjacency A is modified to produce A, which yields a combined convolutional layer that is more straightforward.

$$H=X*g_\theta=f(D^{-\frac{1}{2}}AD^{-\frac{1}{2}}X\Theta) \tag{9}$$

where $A=I+A$ and $D_{ij}=\sum jA_{ij}, f(.)$ is the activation function, and Θ is the matrix of the filter parameters. GCN architecture and algorithm is followed.

2.2. Graph Neural Network

In 2005, a unique neural network model was created that demonstrated the capability to handle graph structure data. This model is known as the graph neural network. The objective of Graph Neural Networks (GNN) is to develop effective deep learning techniques for non-Euclidean spaces.

The following is an introduction to the relevant concepts: the input graph should be $G=(V,E,X_V,X_E)$, $V=\{v_1,v_2,....,v_n\}$ depicts the collection of nodes, and $E=\{(i,j)|when\ v_i\ is\ adjacent\ to\ v_j\}$ is a collection of edges. x_i indicates the feature vector for node v_i, and $X_V=\{x_1,x_2,...,x_n\}$ is the set of all nodes' feature vectors. $x(i,j)$ denotes the feature vector of edge (i,j), and $X_E=\{x_{(i,j)}|(i,j)\in E\}$ is the collection of all edge feature vectors.

In a graph neural network model, the input graph G is turned into a dynamic graph $G^t=(V,E,X_V,X_E,H^t)$, where t = 1, 2,..., T denotes time and $H^t=(h_1^{(t)},h_2^{(t)},....,h_n^{(t)})$, $h_i^{(t)}$, represents the state vectors of node v_i at time t, that is dependent on the graph G^{t-1} at time $t-1$. The $h_i^{(t)}$ equation is as follows:

$$h_i^{(t)}=f_w(x_i,x_{co(i)},h_{ne(i)}^{t-1},x_{ne(i)}) \tag{10}$$

where $f_w(\bullet)$ represents the local transformation function with parameter $w,x_{ne(i)}$ is the set of vectors of features of all nodes adjacent to node $v_i,x_{co(i)}$ is the set of feature vector of all edges linked to node v_i, and $h_{ne(i)}^{(t)}$ is the collection of feature vectors of all edges linked to node vi. The collection of state vector of all nodes that are adjacent to node v_i at time t.

3. Literature Review

This research provides an easy-to-use yield forecast system for farmers. The suggested solution has a smartphone app for farmer communication. Various Machine Learning methods, including SVM, ANN, RF, MLR, and KNN, are used to estimate agricultural production. The Random Forest had the highest accuracy at 95% [21].

This study introduces Agro DSS, a unique system that connects agricultural systems with cutting-edge decision support. Tools include predictive modelling, accuracy assessment, time series grouping, decomposition, and structural change detection. Users may use them to forecast simulated situations and comprehend domain relationships or interconnections [22].

The paper introduces Agro Consultant is a clever system. that helps farmers from India choose crops based on sowing season, farm geographical position, soil properties, and environmental variables like Climate and precipitation. The results of his Multi-Label Classification (MLC) model comparison with KNN and Random Forest showed that it is better for prediction than the existing model [23].

This paper describes a system. of recommendations using A majority-voting ensemble model employing Tree at random, CHAID, and K-nearest Neighbor, as well as Naive Bayes to suggest crops depending on site-specific parameters. that are very effective and accurate. The system uses data on features and kinds of soil, and crop yield to guide farmers in choosing the right crop [24].

The author created a soil-based crop utilizing a recommendation system a combination of ensemble models using majoritarian voting methods such using majoritarian voting methods, the K-Near Naive Bayes to Neighbor pick crops with excellent efficiency and precision. These algorithms assess agricultural productivity under given weather circumstances utilizing statistical data like the environmental factors, agricultural production, and state/district crops to provide categorization pictures [25].

This article discusses AI-driven precision agriculture and a ML-powered and cloud-based agricultural suggestion engine to help farmers grow crops based on data. Extreme

Gradient Boosting, Decision Trees, Random Forests, KNNs, and Support Vector Machines, or SVM, are tested to find the best prediction machine learning (ML) method for a cloud-based recommendations platform. Free, open-source precision agriculture solutions aid development and adoption [26].

Our study aims to solve this problem by creating a machine learning-based recommendation system along with image manipulation. We compared KNN, XGBoost, random forest, as well as neural network-based picture augmentation methods in this article, and discovered XGBoost outperformed the others. The developed model is accurate enough [27].

The goal of this review is to provide a thorough overview of the most recent research projects using deep convolutional neural networks (CNNs) for plant phenotyping applications. We examine especially how different CNN architectures are used to evaluate postharvest quality, monitor plant growth, and measure plant stress. Finally, we provide a number of suggestions for further investigation into the use of CNN architecture to plant phenotyping [28].

The study demonstrated that, in addition to case-specific irrigation and drainage management optimization, combinations of soil amendments, conditioners, and residue management may greatly increase crop yields while reducing soil salinity. These findings demonstrate that greater yields necessary for expanding and maintaining agricultural output may also be obtained via conservation agriculture [29].

In this article, we covered four topics: (1) the effect of conventional and unconventional cropping practices on soil health in agro-systems; (2) the evolution of plant-microbe soil complex and the biochemical mechanisms responsible for soil health under the pressure of agriculture; (3) changes in the notion of soil quality and health over recent decades in agro-systems and the key indicators currently used for evaluating soil health; and (4) problems in agroecosystems that affect soil health [30].

4. Materials and Methods

4.1. Data-Set

In the context of this article, we made use of the data set that can be found at https://www.kaggle.com/datasets/siddharthss/crop-recommendation-dataset.

4.2. Data Preparation to Train GCN

Data preparation to train a Graph Convolutional Network (GCN) entails many critical processes to guarantee that the model can learn successfully from the provided variables, which include edges, features, and targets.

The creation of the graph structure is the initial stage in data preparation. There has to be identification and organization of edges, which describe the connections among nodes in the network. In order to do this, an adjacency matrix must be created to reflect the relationships between nodes. Additionally, node features need to be gathered. These characteristics record data about each node & provide the GCN crucial input. In order to ensure proper information flow in the graph, it is essential to make sure that the node characteristics match up with the associated nodes in an adjacency matrix.

Furthermore, for supervised learning tasks, target labels or values connected to certain nodes are crucial. These targets could represent actual data for regression tasks or categories for node classification. To set the baseline for the learning process, it is essential to match the goal values with their appropriate nodes.

After preparing the graph topology, node characteristics, and goal values, data normalization should be considered. This stage improves training stability as well as convergence. Normalizing features & scaling target values eliminate problems caused by different magnitudes and distributions.

Finally, the data should be separated into three groups: training, validation, and test. Care must be taken to make sure that the structure of graphs stays intact inside each set,

maintaining the data's interconnectedness. Techniques like as stratified sampling are often used to maintain distribution of classes balance, especially for node tasks involving classification.

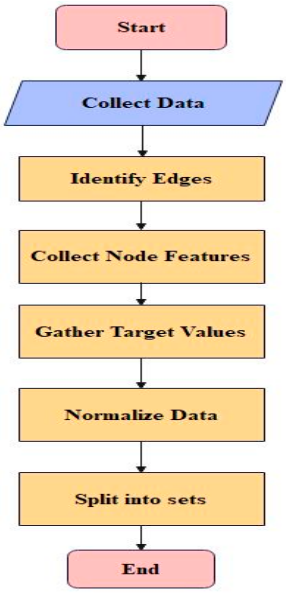


Figure 2. Flow chart of data preparation of GCN.

4.3. Model Training

After preprocessing the data, train the Graph Convolutional Network (GCN) requires many crucial stages. The GCN model has graph convolutional units in each layer. These units transfer messages between neighboring nodes, allowing the model to reflect complex network interactions. The model minimizes a loss function that measures the difference among predicted and target values during training. The backpropagation procedure computes loss gradients with respect to the model's parameters, permitting gradient descent or associated methods for optimization. Dropout or L2 regularization may avoid overfitting. Splitting the training dataset into batches improves memory efficiency and convergence. A validation set continually monitors the model's performance to avoid overfitting and pick the ideal model according to validation criteria. After training converges, the example may be tested on a separate test set for generalization to new data. Hyperparameter tweaking, including learning rate, layers, and hidden units per layer, greatly affects the GCN's predictive capability and convergence behavior, making training successful.

4.4. Model Evaluation

The capacity of a trained model to generalize to new data is assessed through model assessment. Metrics such the F1-score, precision, recall, and accuracy, specificity, & sensitivity reflect categorization task performance. Cross-validation guarantees that estimations are accurate. Confusion matrices, for example, give extensive information. Evaluation guides deployment and improvement.

4.5. Performance Metrics

Accuracy: A simple way to gauge accuracy is to look at how often the classifier predicts correctly. The ratio of the number of accurate forecasts to all of the model's predictions may be used to determine accuracy.

$$Accuracy = \frac{TP + TN}{S}$$

Precision: In terms of the total number of instances that have been categorized, precision is the proportion of cases that are accurately categorized.

$$\Pr ecision = \frac{TP}{TP + FP}$$

Recall: the ratio of the total number of true and false negatives to the correct positive numbers.

$$\mathrm{Re}\, call = \frac{TP}{TP + FN}$$

F1-Score: To compute the F1 score, the harmonic mean of the recall and accuracy scores is determined.

$$F1 = \frac{2 * \Pr ecision * \mathrm{Re}\, call}{\Pr ecision + \mathrm{Re}\, call}$$

Sensitivity: Memory, or sensitivity, is another name for recall, refers to the proportion of properly positive labels that our computer is able to identify as being labels. This percentage may also be expressed as a percentage.

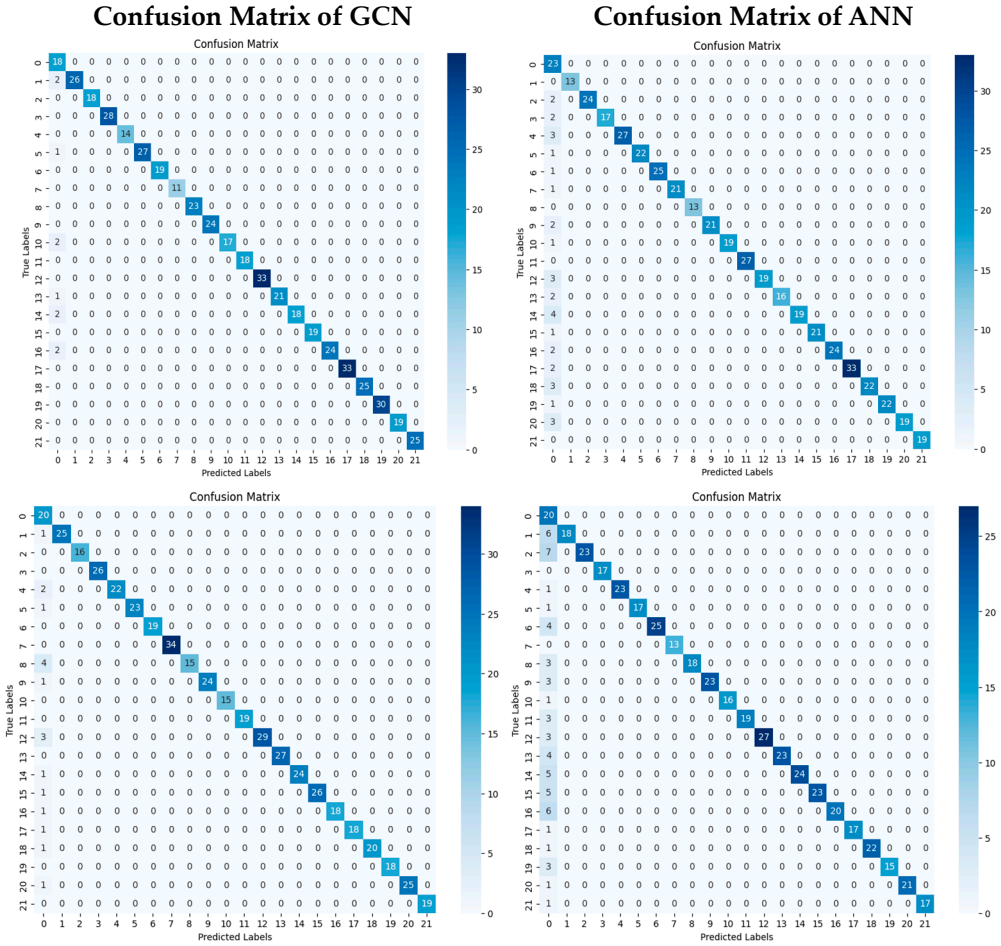
$$Sensitivity = \frac{TP}{TP + FN}$$

Specificity: The algorithm has identified the negative as specificity, which is the proper classification.

$$Specificity = \frac{TN}{TN + FP}$$

5. Results

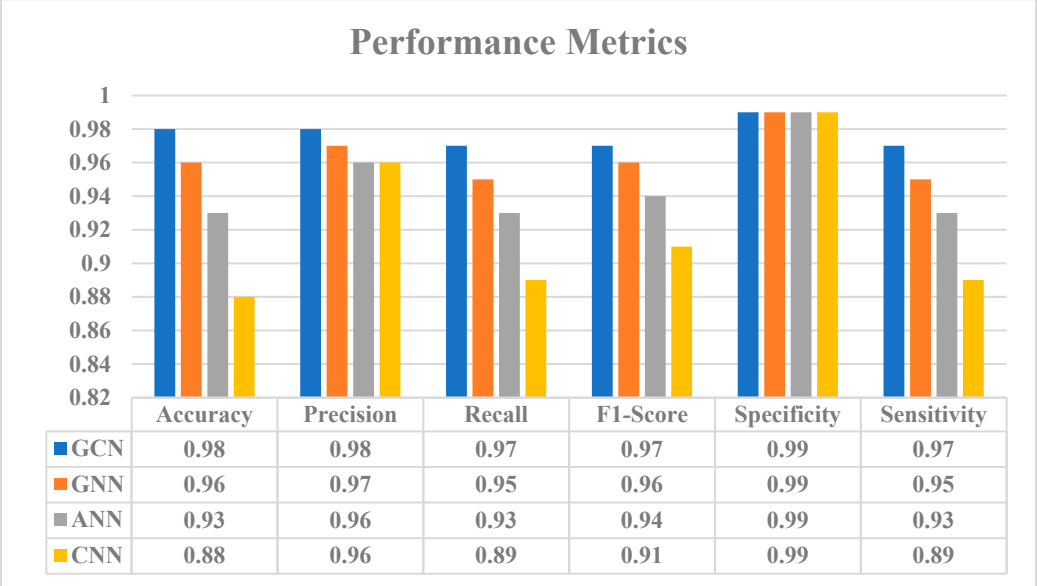
From the table below, there are 22 classes, from 0 to 21. Class 0 is the crop rice, Class 1 is the crop wheat, and Class 2 is the crop maize. 1—represent the crop of corn, 2—represent the crop of chickpeas, 3—represent the crop of kidney beans, 4—represent the crop of pigeon peas, 5—represent the crop of moth beans. 6—is a crop called mung bean, 7—stands for the black gramme, 8—stands for the bean, the number 9 stands for the grape, 10: Show the banana, The number 11 stands for the mango, the number 12 for the grapes, the number 13 for the watermelon, the number 14 for the muskmelon, and the number 15 for the apple. 16 stands for the orange, 17 stands for the papaya, 18 stands for the coconut, 19, for the cotton, 20, for the jute, and 21, for the coffee.



Considering the provided ambiguity matrix, it can be observed that the proposed GCN model obtained a classification accuracy of 492 out of 500 samples, with 8 misclassified instances. In comparison, the existing CNN model achieved a correct classification rate of 482 out of 500 samples, with 18 misclassified instances. The ANN model obtained a classification accuracy rate of 447 out of 500 samples, with 53 misclassified instances. Lastly, the CNN the model had a successful classification rate of 441 out of 500 samples, with 59 misclassified instances. Based on our analysis, it can be concluded that the suggested model, Graph Convolutional Network (GCN), has a higher level of accuracy in classification tasks, resulting in a reduced number of misclassifications, as compared to other models.

Table 1. Performance Metrics.

Model	Accuracy	Precision	Recall	F1-Score	Specificity	Sensitivity
GCN	0.98	0.98	0.97	0.97	0.99	0.97
GNN	0.96	0.97	0.95	0.96	0.99	0.95
ANN	0.93	0.96	0.93	0.94	0.99	0.93
CNN	0.88	0.96	0.89	0.91	0.99	0.89



	Accuracy	Precision	Recall	F1-Score	Specificity	Sensitivity
GCN	0.98	0.98	0.97	0.97	0.99	0.97
GNN	0.96	0.97	0.95	0.96	0.99	0.95
ANN	0.93	0.96	0.93	0.94	0.99	0.93
CNN	0.88	0.96	0.89	0.91	0.99	0.89

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6. Discussion

The GCN (Graph Convolutional Network) model is clearly better than other crop recommendation models, as shown by the performance metrics shown in Table 1. The GCN model, which has an amazing accuracy rate of 0.98, not only performs well in this important measure but also routinely achieves excellent results in a number of other crucial assessment criteria, including as accuracy, recall, F1-score, specificity, & sensitivity. The unique ability of the GCN model to see the vast network of data related to agriculture through a lens of graphs topologies, so capturing intricate interconnections that are frequently elusive via conventional models, is what really sets it apart. Because of its amazing capacity for translating abstract knowledge into practical insights, the GCN model has the potential to revolutionize agricultural decision-making. The model provides stakeholders with essential information to optimize plans and resource allocation by providing individualized and knowledgeable crop suggestions. In simple terms, the GCN model's strength goes beyond quantitative measurements. It has the potential to fundamentally alter the way we think about agriculture, ushering in a time where improving yields, long-term viability and overall production will be driven by data-driven intelligence. The GCN model's superior ability to comprehend complex data structures sheds a positive light on the future of the agricultural sector, where innovation and pragmatism are combined for the benefit of the sector and the security of the world's food supply.

7. Conclusions

Finally, the extensive research reported in Table 1 supports the GCN (Graph Convolutional Network) model as the indisputable leader in crop recommendation tasks.

The GCN model, with an amazing 98% accuracy rate, establishes an incredibly high standard that is routinely matched by great performance across a range of essential measures such as recall, precision, F1-score, specificity, then & sensitivity. This comprehensive study not only confirms the GCN model's superiority, but also highlights its potential to transform the landscape and agricultural decision-making. The GCN model's unique capacity to untangle the complexities of agricultural data using graph topologies gives a multidimensional view unmatched by its competitors. This distinguishing feature enables it to provide personalized and contextually appropriate crop advice with remarkable granularity. The comparison analysis emphasizes the GCN model's clear advantage over competing models, establishing it as the only viable option for constructing an efficient crop recommendation system. The GCN model possesses the potential to optimize the use of resources, improve sustainability practices, and significantly increase agricultural output by leveraging the power of modern data analytic tools. Its ability to achieve an accuracy rate of 98% attests to its resilience and highlights its position as a cornerstone in moving the area of precision agriculture ahead. In a world of changing difficulties and agricultural needs, the GCN model's capacity to deliver insightful and exact suggestions is a spark of innovation. As technology continues to alter agriculture's future, the GCN model's efficacy highlights its critical contribution, highlighting its importance in driving transformative change in crop management and supporting a more environmentally friendly and productive agricultural industry.

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