


# Crop Recommendation Systems Based on Soil and Environmental Factors Using Graph Convolution Neural Network: A Systematic Literature Review <sup>†</sup>

P. Ayesha Barvin  and T. Sampradeepraj \* 

Department of Computer Science and Engineering, Kalasalingam Academy of Research and Education, Srivilliputhur 626138, Tamil Nadu, India; r9923104006@klu.ac.in

\* Correspondence: t.sampradeepraj@klu.ac.in

<sup>†</sup> Presented at the 10th International Electronic Conference on Sensors and Applications (ECSA-10), 15–30 November 2023; Available online: <https://ecsa-10.sciforum.net/>.

**Abstract:** Data-driven approaches and resource management to improve yield are becoming increasingly frequent in agriculture with the progress in technology. Based on a broad variety of environmental variables, this research compares two graph-based crop recommendation algorithms, GCN and GNN. Our methods select the optimal crop for a season based on nitrogen, potassium and phosphorus levels, as well as temperature, humidity, soil pH and rainfall. We assess the dataset's complexity using GCN and GNN, which can 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 optimal crop based on 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 highlights their potential to enhance precision agriculture. We prioritize 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



**Citation:** Ayesha Barvin, P.; Sampradeepraj, T. Crop Recommendation Systems Based on Soil and Environmental Factors Using Graph Convolution Neural Network: A Systematic Literature Review. *Eng. Proc.* **2023**, *58*, 97. <https://doi.org/10.3390/ecsa-10-16010>

Academic Editor: Stefano Mariani

Published: 15 November 2023



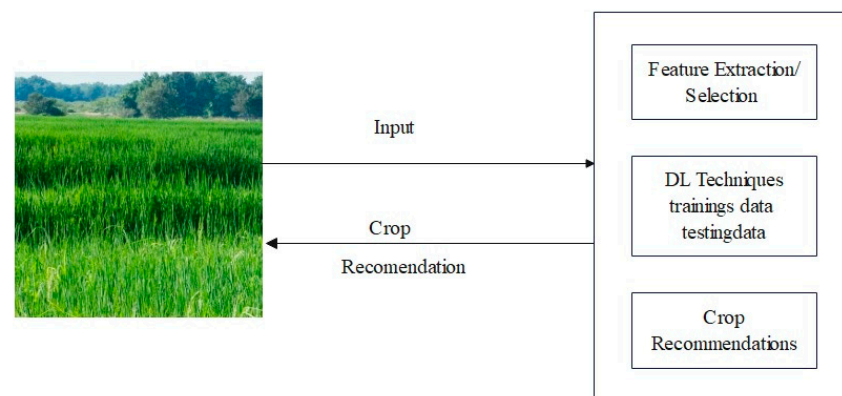
**Copyright:** © 2023 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

## 1. Introduction

India is the leading producer of agricultural goods. The agriculture industry employs 58 percent of the total Indian population as well as contributes 17% to the country's GDP. Crops rely on a multitude of factors, including the type of soil, amount of rainfall and sunlight, irrigation, fertilizer use, insect presence, and land preparation [1,2]. One of the most frequent challenges that Indian farmers must overcome is choosing crops in accordance with the terrain and the climate [3]. Considering the fact that climatic conditions and characteristics of 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 practices may help increase productivity and produce quality crops [5].

Precision agriculture has recently brought about significant advances in the world of agriculture, with an emphasis on irrigation systems, fertilization, 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 suited for the region's unique meteorological and soil conditions [8]. The development of crop recommendation system using deep learning techniques are illustrated in Figure 1. 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 crop recommendation systems that consider location-specific factors. The research described in this article tries to create a recommendation algorithm that offers highest 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 developing a crop recommendation system that depends on terrain and environmental factors [11].



**Figure 1.** Crop recommendation system using deep learning.

## 2. Background

In this section, we discuss the proposed model graph convolution network (GCN) and the existing model graph neural network (GNN) along with their architectures.

### 2.1. Graph Convolution Network (GCN)

Graph-based neural networks, an extension of deep neural network models designed for data with inherent graph structures, have seen a surge in popularity in recent years. This trend is particularly notable in conjunction with the field of link prediction [12,13].

Consider a weighted undirected graph  $G$ , represented by its adjacency matrix  $A$ , where  $A(i, j)$  in the  $i$ th row and  $j$ th column signifies the weight of the edge  $(i, j)$ . The degree matrix,  $D$ , is defined as follows:

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

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

$$L = I - D^{-\frac{1}{2}} A D^{-\frac{1}{2}} \quad (2)$$

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

$$L = U \Lambda U^T \quad (3)$$

where  $U = (u_0, u_1, \dots, u_{n-1})$  is the matrix of eigenvectors and  $\Lambda = \begin{bmatrix} \lambda_1 & \dots & 0 \\ \dots & \dots & \dots \\ 0 & \dots & \lambda_n \end{bmatrix}$  is

the eigenvalues diagonal matrix. As shown by the Fourier transform ecosystem on the graph, the normalized Laplacian matrix,  $L$ , and its eigenvector,  $u$ , creates an orthogonal space [14,15]. The vector of features of each node in the graph represented by the graph

signal is  $x = (x_0, x_1, \dots, x_{n-1}) \in R^n$ . The Fourier transform of the graph signal,  $x$ , is shown below.

$$\hat{x} = U^T x \quad (4)$$

The convolution of the two signals is calculated as follows:

$$x * g = U((U^T x)(U^T g)) \quad (5)$$

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

$$x * g_\theta = U g_\theta (\wedge) U^T x \quad (6)$$

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.

$$g_\theta = \sum_{k=0}^K \theta_k \lambda_l^k \quad (7)$$

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  $O(K) = O(1)$  [16,17]. 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 obtained as follows:

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

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

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

where  $\tilde{A} = I + A$  and  $D_{ij} = \sum_j \tilde{A}_{ij}$ ,  $f(\cdot)$  is the activation function and  $\Theta$  is the matrix of the filter parameters. The 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 (GNNs) is to develop effective deep learning techniques for non-Euclidean spaces [18,19].

The following is an introduction to the relevant concepts. The input graph is  $G = (V, E, X_V, X_E)$ ,  $V = \{v_1, v_2, \dots, v_n\}$ , which depicts the collection of nodes, and  $E = \{(i, j) \mid \text{when } v_i \text{ is adjacent to } v_j\}$  is a collection of edges.  $x_i$  indicates the feature vector for node  $v_i$ , and  $X_V = \{x_1, x_2, \dots, x_n\}$  is the set of all nodes’ feature vectors.  $x(i, j)$  denotes the feature vector of edge  $(i, j)$ , and  $X_E = \{x(i, j) \mid (i, j) \in E\}$  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  $t = 1, 2, \dots, T$  denotes time and  $H^t = (h_1^{(t)}, h_2^{(t)}, \dots, h_n^{(t)})$ .  $h_i^{(t)}$  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:

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

where  $f_w(\cdot)$  represents the local transformation function with parameters;  $w, x_{ne(i)}$  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  $v_i$ ;  $h_{ne(i)}^{(t)}$  is the collection of feature vectors of all edges linked to node  $v_i$ ; and the collection of state vector of all nodes that are adjacent to node  $v_i$  at time  $t$  [20].

### 3. Literature Review

This research unveils a straightforward yield forecast system crafted for the convenience of farmers. The proposed solution takes the form of a smartphone app, acting as a communicative tool to inform farmers about the myriad factors influencing crop yield. Various machine learning methods, including SVM, ANN, RF, MLR and KNN, are used to estimate agricultural production. The random forest method had the highest accuracy at 95% [21].

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

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

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

The authors developed a crop recommendation system based on soil characteristics, employing a blend of ensemble models and majoritarian voting methods like K-nearest neighbor and naive Bayes. This approach aims to select crops with high efficiency and precision. These algorithms assess agricultural productivity under given weather circumstances utilizing statistical data like environmental factors, agricultural production and state/district crops to provide categorization pictures [25].

This article discusses AI-driven precision agriculture and an ML-powered cloud-based agricultural suggestion engine to help farmers grow crops based on data. Extreme gradient boosting, decision tree, random forest, KNN and support vector machine (SVM) methods are tested to find the best prediction machine learning (ML) method for a cloud-based recommendation platform. The advancement and widespread use of free and open-source precision agriculture solutions contribute to the cultivation and acceptance of high-quality crops [26].

Our study aims to solve the problem of choosing optimal crops 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 that XGBoost outperformed the other models. 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 particularly examine 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 for plant phenotyping [28].

This study demonstrated that, in addition to case-specific irrigation and drainage management optimization, combinations of soil amendments, conditioners and residue

management may significantly increase crop yields while reducing soil salinity. These findings demonstrate that higher 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 agrosystems; (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 in recent decades in agrosystems and the key indicators currently used for evaluating soil health; and (4) the problems in agroecosystems that affect soil health [30].

## 4. Materials and Methods

### 4.1. Dataset

In this article, we used the following data set that can be found at <https://www.kaggle.com/datasets/siddharthss/crop-recommendation-dataset> (accessed on 21 August 2023). This dataset was built by augmenting datasets of rainfall, climate and fertilizer data available for India. The dataset which would allow the users to build a predictive model to recommend the most suitable crops to grow in a particular farm based on various parameters.

### 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 successfully learn from the provided variables, which include edges, features and targets.

The creation of the graph structure is the initial stage of data preparation. This will include identification and organization of edges, which describe the connections among the 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 features record data about each node and 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 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.

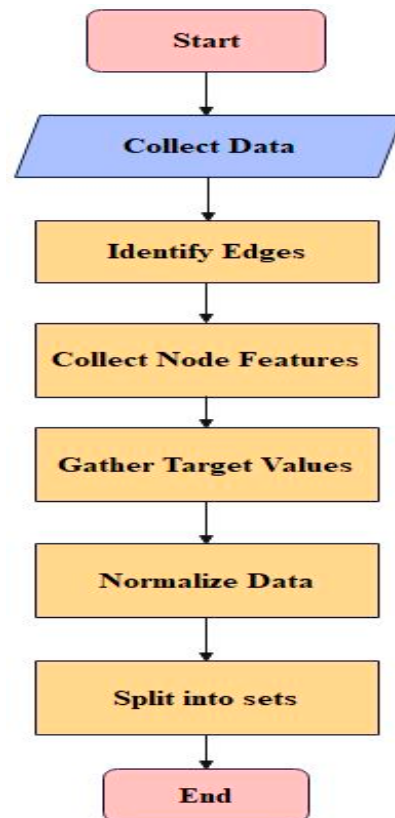
After preparing the graph topology, node characteristics and goal values, data normalization should be considered. This stage improves training stability as well as convergence. Normalizing features and scaling target values eliminate problems caused by different magnitudes and distributions.

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 such as stratified sampling are often used to maintain distribution of classes balance, especially for node tasks involving classification. Figure 2 depicts the flow chart for proposed methodology.

### 4.3. Model Training

After preprocessing the data, the graph convolutional network (GCN) requires many crucial training 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. This 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 picks the ideal model according to the validation criteria. After training

converges, the example may be tested on a separate test set for generalization to new data. Hyper parameter tweaking, including learning rate, layers and hidden units per layer, significantly affects the GCN's predictive capability and convergence behavior, thereby making training successful.



**Figure 2.** Flow chart of GCN data preparation.

#### 4.4. Model Evaluation

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

$$Precision = \frac{TP}{TP + FP}$$

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

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



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

$$F1 = \frac{2 * Precision * Recall}{Precision + Recall}$$

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

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

Specificity: The algorithm identifies the negative labels as specificity, which is the proper classification.

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

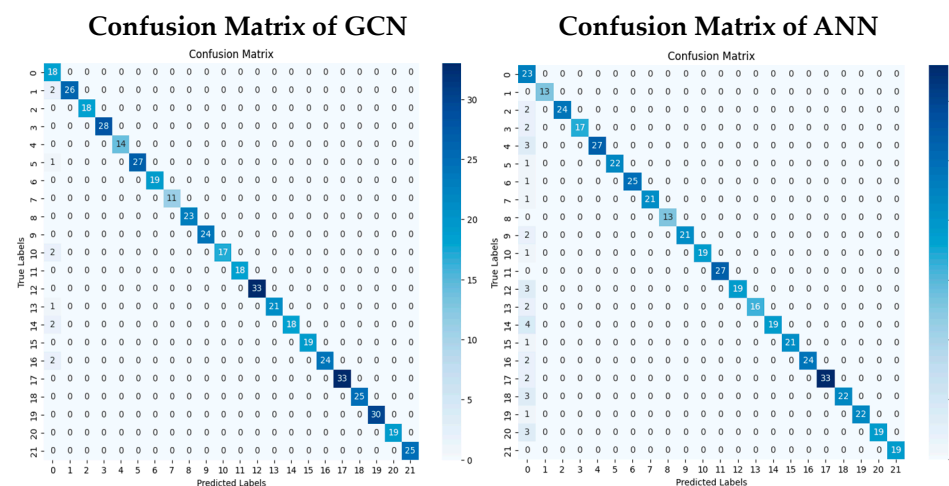
## 5. Results

From Table 1 below, it can be seen that there are 22 classes, from 0 to 21. Class 0 is rice, Class 1 is wheat, and Class 2 is maize. The samples are as follows: 1—corn, 2—chickpeas, 3—kidney beans, 4—pigeon peas, 5—moth beans, 6—mung bean, 7—black gramme, 8—bean, 9—grape, 10—banana, 11—mango, 12—grapes, 13—watermelon, 14—muskmelon, 15—apple, 16—orange, 17—papaya, 18—coconut, 19—cotton, 20—jute and 21—coffee.

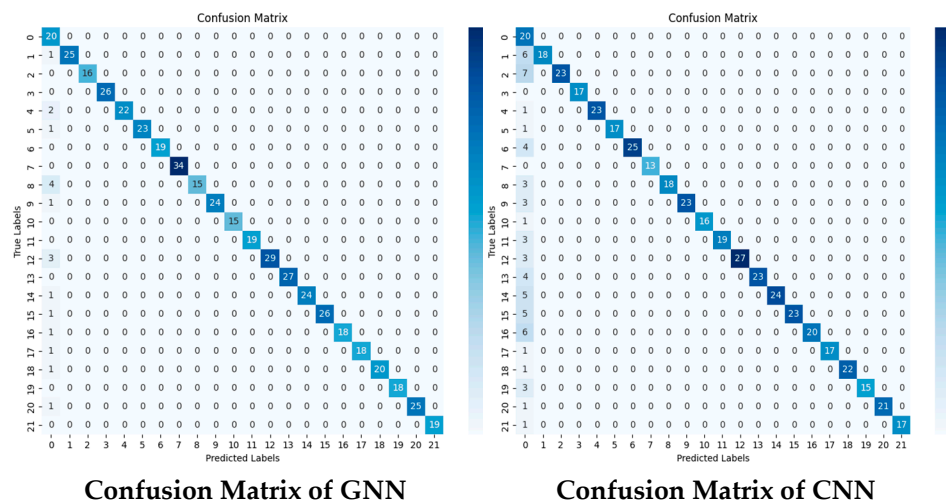
**Table 1.** Performance metrics.

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

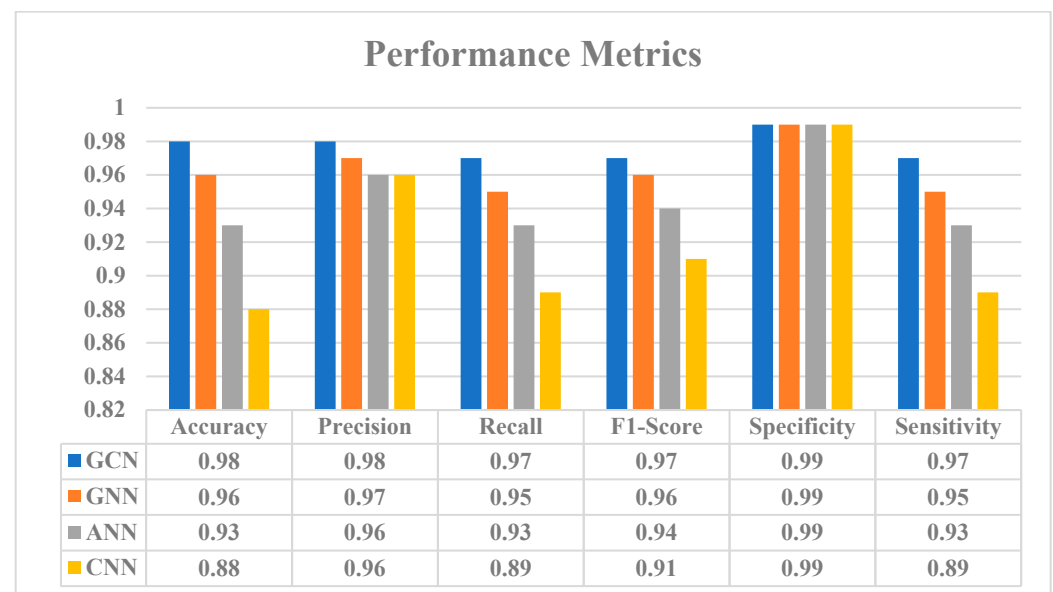
Figure 3 illustrates the confusion matrices for the proposed Graph Convolutional Network (GCN) and established methods like GNN, CNN), and ANN. Notably, the GCN exhibits the highest accuracy in correct predictions and a notably lower incidence of misclassifications compared to the other existing methods. Our analysis leads to the conclusion that the suggested model, the Graph Convolutional Network (GCN), demonstrates superior accuracy in classification tasks by minimizing misclassifications when compared to alternative models. Figure 4 depicts the comparison of performance metrics of proposed and existing methods.



**Figure 3.** Cont.



**Figure 3.** Comparison of proposed and existing methods.



**Figure 4.** Comparison of performance metrics.

## 6. Discussion

The GCN (graph convolutional network) model is clearly better than other crop recommendation models, as shown by the performance metrics in Table 1. The GCN model, which has a significantly higher 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 accuracy, recall, F1-score, specificity and sensitivity. The unique ability of the GCN model to analyze the vast network of data related to agriculture through a lens of graphs topologies, thereby 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. This model provides stakeholders with essential information to optimize plans and resource allocation by providing individualized and informed 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 led 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

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 and 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 potential for moving further improving precision agriculture. 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 demonstrates its critical contribution, highlighting its importance in driving transformative change in crop management and supporting a more environmentally friendly and productive agricultural industry.

**Author Contributions:** Conceptualization and methodology, and writing are done by P.A.B.; Resources, investigation, analysis part are done by T.S. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research was conducted without external funding or financial support.

**Institutional Review Board Statement:** Not applicable.

**Informed Consent Statement:** Not applicable.

**Data Availability Statement:** In this research, we used kaggle website, where data supporting reported results can be found, including crop related images are used during the study. In this article, we used the following data set that can be found at <https://www.kaggle.com/datasets/siddharthss/crop-recommendation-dataset>.

**Conflicts of Interest:** The authors declare no conflict of interest.

## References

1. Tugrul, B.; Elfatimi, E.; Eryigit, R. Convolutional Neural Networks in Detection of Plant Leaf Diseases: A Review. *Agriculture* **2022**, *12*, 1192. [CrossRef]
2. Bandara, P.; Weerasooriya, T.; Ruchirawya, T.; Nanayakkara, W.; Dimantha, M.; Pabasara, M. Crop recommendation system. *Int. J. Comput. Appl.* **2020**, *975*, 8887. [CrossRef]
3. Sivanandhini, P.; Prakash, J. Crop Yield Prediction Analysis using Feed Forward and Recurrent Neural Network. *Int. J. Innov. Sci. Res. Technol.* **2020**, *5*, 1092–1096.
4. Pruthviraj; Akshatha, G.C.; Shastry, K.A.; Nagaraj; Nikhil. Crop and fertilizer recommendation system based on soil classification. In *Recent Advances in Artificial Intelligence and Data Engineering, Proceedings of AIDE 2020, Karkala, India, 22–23 December 2020*; Springer: Berlin/Heidelberg, Germany, 2022; pp. 29–40.
5. Motwani, A.; Patil, P.; Nagaria, V.; Verma, S.; Ghane, S. Soil Analysis and Crop Recommendation using Machine Learning. In *Proceedings of the 2022 International Conference for Advancement in Technology (ICONAT)*, IEEE, Goa, India, 21–22 January 2022; pp. 1–7.
6. Sharma, A.; Bhargava, M.; Khanna, A.V. AI-Farm: A crop recommendation system. In *Proceedings of the 2021 International Conference on Advances in Computing and Communications (ICACC)*, IEEE, Kochi, Kakkannad, India, 21–23 October 2021; pp. 1–7.

7. Bandi, R.; Likhith, M.S.S.; Reddy, S.R.; Bodla, S.R.; Venkat, V.S. Voting Classifier-Based Crop Recommendation. *SN Comput. Sci.* **2023**, *4*, 516. [\[CrossRef\]](#)
8. Fassa, V.; Pricca, N.; Cabassi, G.; Bechini, L.; Corti, M. Site-specific nitrogen recommendations' empirical algorithm for maize crop based on the fusion of soil and vegetation maps. *Comput. Electron. Agric.* **2022**, *203*, 107479. [\[CrossRef\]](#)
9. Shedthi, S.; Shetty, A.; Shetty, R.R.; Alva, B.A.D.; Shetty, A.D. Machine Learning Techniques in Crop Recommendation based on Soil and Crop Yield Prediction System—Review. In Proceedings of the 2022 International Conference on Artificial Intelligence and Data Engineering (AIDE), IEEE, Karkala, Karnataka, India, 22–23 December 2022; pp. 230–235.
10. Hossain, D.; Kashem, M.A.; Mustary, S. IoT Based Smart Soil Fertilizer Monitoring and ML Based Crop Recommendation System. In Proceedings of the 2023 International Conference on Electrical, Computer and Communication Engineering (ECCE), London, UK, 11–12 December 2023; pp. 1–6.
11. Banerjee, S.; Mondal, A.C. A Region-Wise Weather Data-Based Crop Recommendation System Using Different Machine Learning Algorithms. *Int. J. Intell. Syst. Appl. Eng.* **2023**, *11*, 283–297.
12. Zhou, J.; Cui, G.; Hu, S.; Zhang, Z.; Yang, C.; Liu, Z.; Wang, L.; Li, C.; Sun, M. Graph neural networks: A review of methods and applications. *AI Open* **2020**, *1*, 57–81. [\[CrossRef\]](#)
13. Zhu, J.; Rossi, R.A.; Rao, A.; Mai, T.; Lipka, N.; Ahmed, N.K.; Koutra, D. Graph neural networks with heterophily. In Proceedings of the AAAI Conference on Artificial Intelligence, Vancouver, BC, Canada, 2–9 February 2021; pp. 11168–11176.
14. Zheng, X.; Liu, Y.; Pan, S.; Zhang, M.; Jin, D.; Yu, P.S. Graph neural networks for graphs with heterophily: A survey. *arXiv* **2022**, arXiv:2202.07082.
15. Wu, Z.; Pan, S.; Chen, F.; Long, G.; Zhang, C.; Yu, P.S. A comprehensive survey on graph neural networks. *arXiv* **2019**, arXiv:1901.00596. [\[CrossRef\]](#) [\[PubMed\]](#)
16. Scarselli, F.; Gori, M.; Tsoi, A.C.; Hagenbuchner, M.; Monfardini, G. The graph neural network model. *IEEE Trans. Neural Netw.* **2008**, *20*, 61–80. [\[CrossRef\]](#) [\[PubMed\]](#)
17. Zhang, X.-M.; Liang, L.; Liu, L.; Tang, M.-J. Graph Neural Networks and Their Current Applications in Bioinformatics. *Front. Genet.* **2021**, *12*, 690049. [\[CrossRef\]](#) [\[PubMed\]](#)
18. Chen, M.; Wei, Z.; Huang, Z.; Ding, B.; Li, Y. Simple and deep graph convolutional networks. In Proceedings of the International Conference on Machine Learning, PMLR, Virtual, 13–18 July 2020; pp. 1725–1735.
19. Tong, Z.; Liang, Y.; Sun, C.; Rosenblum, D.S.; Lim, A. Directed graph convolutional network. *arXiv* **2020**, arXiv:2004.13970.
20. Ma, Y.; Hao, J.; Yang, Y.; Li, H.; Jin, J.; Chen, G. Spectral-based graph convolutional network for directed graphs. *arXiv* **2019**, arXiv:1907.08990.
21. Pande, S.M.; Ramesh, P.K.; Anmol, A.; Aishwarya, B.R.; Rohilla, K.; Shaurya, K. Crop Recommender System Using Machine Learning Approach. In Proceedings of the 2021 5th International Conference on Computing Methodologies and Communication (ICCMC), Erode, India, 8–10 April 2021; pp. 1066–1071.
22. Rupnik, R.; Kukar, M.; Vračar, P.; Košir, D.; Pevec, D.; Bosnić, Z. AgroDSS: A decision support system for agriculture and farming. *Comput. Electron.* **2009**, *161*, 260–271. [\[CrossRef\]](#)
23. Doshi, Z.; Nadkarni, S.; Agrawal, R.; Shah, N. AgroConsultant: Intelligent Crop Recommendation System Using Machine Learning Algorithms. In Proceedings of the 2018 Fourth International Conference on Computing Communication Control and Automation (ICCUBEA), Pune, India, 16–18 August 2018; pp. 1–6.
24. Pudumalar, S.; Ramanujam, E.; Rajashree, R.H.; Kavaya, C.; Kiruthika, T.; Nisha, J. Crop recommendation system for precision agriculture. In Proceedings of the 2016 Eighth International Conference on Advanced Computing (ICoAC), Chennai, India, 19–21 January 2017; pp. 32–36. [\[CrossRef\]](#)
25. Reddy, D.A.; Dadore, B.; Watekar, A. Crop Recommendation System to Maximize Crop Yield in Ramtek region using Machine Learning. *Int. J. Sci. Res. Sci. Technol.* **2019**, *6*, 485–489. [\[CrossRef\]](#)
26. Thilakarathne, N.N.; Abu Bakar, M.S.; Abas, P.E.; Yassin, H. A Cloud Enabled Crop Recommendation Platform for Machine Learning-Driven Precision Farming. *Sensors* **2022**, *22*, 6299. [\[CrossRef\]](#) [\[PubMed\]](#)
27. Chakraborty, S.; Mishra, S. A Smart Farming-Based Recommendation System Using Collaborative Machine Learning and Image Processing. In *Cognitive Informatics and Soft Computing, Proceedings of CISC 2021, Balasore, India, 21–22 August 2021*; Springer: Singapore, 2022; pp. 703–716.
28. Jiang, Y.; Li, C. Convolutional Neural Networks for Image-Based High-Throughput Plant Phenotyping: A Review. *Plant Phenomics* **2020**, *2020*, 4152816. [\[CrossRef\]](#) [\[PubMed\]](#)
29. Cuevas, J.; Daliakopoulos, I.N.; del Moral, F.; Hueso, J.J.; Tsanis, I.K. A Review of Soil-Improving Cropping Systems for Soil Salinization. *Agronomy* **2019**, *9*, 295. [\[CrossRef\]](#)
30. Yang, T.; Siddique, K.H.; Liu, K. Cropping systems in agriculture and their impact on soil health—A review. *Glob. Ecol. Conserv.* **2020**, *23*, e01118. [\[CrossRef\]](#)

**Disclaimer/Publisher's Note:** The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.