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GCN-CRS: Performance Evaluation of Crop Recommendation System using Graph Convolutional Neural Network

Souradeep Sarkar
School of Computer Engineering
Kalinga Institute of Industrial Technology
Bhubaneswar, India
souradeep98sarkar@gmail.com

Abhaya Kumar Sahoo
School of Computer Engineering
Kalinga Institute of Industrial Technology
Bhubaneswar, India
abhaya.sahoofcs@kiit.ac.in

***Abstract*—Precision agriculture enhances the production of crop by exploiting data driven decision making. Traditional crop recommendation systems often passes over the spatial dependencies among regions, resulting poor predictions. This paper suggests Graph Convolutional Neural Network (GCN) based Crop Recommendation System that incorporates the various soil parameters such as pH, phosphorous, nitrogen, potassium, climatic factors such as temperature, rainfall, humidity and environmental conditions to increase the crop selection. By shaping agricultural regions as interconnected nodes in a graph, the system apprehends spatial relationships and raises the accuracy of recommendation. The experimental result manifests that GCN-based model excels traditional models for making a reliable tool for supportable agriculture.**

***Index Terms*—Crop Recommendation, Environmental Factors, Graph Convolutional Neural Network,Precision Agriculture, Soil Analysis**

I. Introduction

Now a days, selection of right crop at appropriate region is very important, specially based on soil quality, weather condition and different environmental factors that help to increase productivity and sustainability. Traditional crop recommendation systems are depending on usually expert's opinion and predefined rules that often fail to recommendation of right crop. To overcome this problem, we have introduced a new generation crop recommendation system using Graph Convolutional Neural Network (GCN) where intelligent decision is made on the basis of real-time crop data and differential environmental factors. GCNs are deep learning models targeted towards graph-structured data, making them highly applicable in agricultural domains, where the relationships between geographical regions, soil characteristics, and climate conditions are critical considerations. In a systematic way to enhance crop choices, the integrated GCN algorithm fuses soil composition, meteorological data, temperature, humidity, and rainfall data to model spatial dependencies of cued recipes to recommend each plant group's recommended crop options [1] [2]. This AI-integrated methodology represents an enhanced traditional system, which has the opportunity to improve prediction accuracy, resource efficiency, and sustainable agriculture practices [3] [4]. This also places farmers in the position to make evidence-based decisions to mitigate risks and pull harvests. The use of integrated GCN computing in farming marks a substantive step towards precision agriculture, demonstrating a scalable and adaptable global approach to food insecurity [1] [5] [6].

This paper describes the purpose and goal of the proposed work in Section II. Section III describes the methodology and implementation, Section IV deals with the performance metrics, Section V presents the investigation of the results, and in the last section, Section VI offers the conclusion and discusses future work.

II. Aim & Objectives:

The main objective of this paper is to design a Crop Recommendation System using Graph Convolutional Neural Graph Convolutional Networks to enhance agricultural decision-making by It analyzes soil and environmental factors. The system aims to accurate and data-driven suggestions on crop improvement yield, resource efficiency, and sustainability in modern farming [7] [5].

A. Objectives:

The aim of this paper is stated below: (i) To analyze soil and environmental factors, data are Collected and processed data on pH, temperature, rainfall, and humidity using sensors based on satellites and the Internet of Things [8]. (ii) Graph Convolutional Neural Networks Implementation GCN: Graph Convolution Networks are utilized to model the spatial relationships. between geographical regions and crop suitability and It is further improved in deep learning methods. (iii) To build an intelligent crop recommendation system. In this scenario, an AI-powered system is built that suggests the best crop-related decisions based on real-time and historical data, and adaptability. can be ensured to dynamic environmental changes. iv) Enhancement of productivity and sustainability of agriculture. Farmers can be helped to make informed decisions, and risk can be reduced, and crop yield can be improved. Precision farming These could be incentivized to reduce waste of resources and enhance food security. This research aims at revolutionizing traditional wheat improvement methodologies by incorporating artificial intelligence. spatial analysis, and environmental science for smarter and more efficient agriculture [3] [5].

III. Methodology & Implementation

- Methodology: The proposed Crop Prediction System employs Graph Convolutional Neural Networks (GCN) to evaluate environmental and soil data for crop forecasting correctly which is shown in is mentioned in "Fig. 1." . The procedure is divided into the following steps:

- Data Collection: Soil parameters, pH, moisture, organic content, texture, and also environmental ones-temperature, rainfall, humidity is assembled, along with real-time data. leveraging satellite imagery and IoT-based sensors are also gathered.

- Data Preprocessing: Data are cleaned and normalized for Consistency and further represented into a graph format where geographical locations are nodes and spatial relationships are edges.

- Graph development & Feature Extraction: A graph-based model is developed to represent soil and climate data. Then, features relevant for impacting the crop are extracted and choices.

- Model Training using GCN: The model is trained with a Graph Convolutional Network (GCN) to model the spatial dependencies between areas. Train the GCN on labelled datasets with existing crop yield and climatic conditions.

- Layer Architecture: The GCN-CRS Model is designed to learn and process graph-structured agricultural data. While the number of layers and their configurations are not clearly indicated in the Below is a standard architecture of the GCN model: summary provided. In such applications, this normally includes:

  Input Layer: Receives feature vectors representing agriculture-related data points, such as soil characteristics, climate Conditions.

Graph Convolutional Layers: These layers perform Message passing among nodes, representing different different regions or conditions to aggregate information from neighborhood nodes, capturing spatial dependencies.

Fully Connected Layers: After graph convolutions, The fully connected layers are used to process the aggregated information and generate predictions.

Output Layer: The final recommendation is generated. showing whether a certain crop is suitable for the specified region.

Activation Functions: The model uses Rectified Linear Unit (RELU) activation functions. ReLU is is commonly used in GCNs for its simplicity and effectiveness at introducing non-linearity to enable the model to capture and learn complex patterns within the data.

Training Parameters: While specific training parameters are not detailed in the available summary. typical training configurations for GCNs include:

Optimizer: Adam is used for its adaptive learning rate capabilities.

Loss Function: Cross-entropy loss is used for classification problems, while mean squared error (MSE) is used for regression tasks.

Evaluation Metrics: Model performance is evaluated using accuracy, precision, recall, and the F1-score.

The GCN-CRS model outperforms traditional machine learning approaches such as Random Forest RF, and SVM, reaching the accuracy of 92.8% accuracy, 91.2% precision, and 90.7% recall

- Crop Recommendation & Validation: It predicts most suitable crop for a given region. Validate the accuracy using test data sets and real-time field data.

- Implementation: The system is deployed as a web-based. or mobile application that would allow farmers to input location data and receive AI-driven crop recommendations. This The approach enhances precision farming, improving yield. This would also ensure that resources are used efficiently and in a manner that is sustainable.

- Model Evaluation: Evaluation of the model addresses limits the generalization capabilities of a trained model. The model performance on the classification tasks is evaluated using relevant metrics such as F1-score, precision, recall, accuracy, specificity, and sensitivity. Besides, Using cross-validation to assure reliable estimations, the the use of a confusion matrix adds depth to the evaluation. The evaluation will help in informing the model deployment of the model, and ongoing improvement.

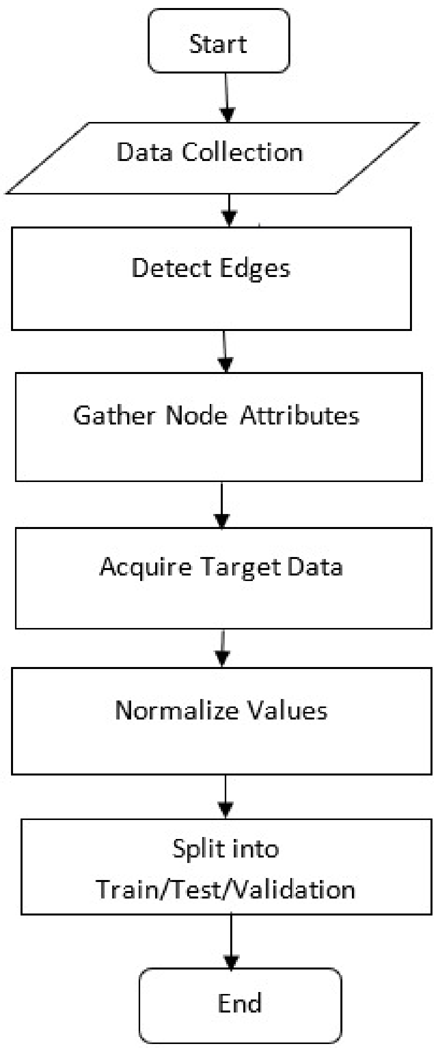

Fig. 1. Workflow Diagram for Preparing Data for GCN

IV. Performance Metrics:

- Accuracy: A straightforward way to measure accuracy is to measure the frequency of a classifier's correct predictions. Accuracy is calculated as the proportion of correctly predicted instances to the overall number of model predictions. "Equation (1)"specifies the accuracy.

TABLE I
Performance metrics

S.N.	Model	Accuracy	Precision	Recall	F1-Score	Specificity	Sensitivity
1	GCN	0.99	0.97	0.96	0.96	0.98	0.96
2	GNN	0.97	0.96	0.96	0.97	0.97	0.94
3	ANN	0.92	0.95	0.94	0.95	0.96	0.94
4	CNN	0.89	0.97	0.88	0.92	0.98	0.87

$$Accuracy = \frac{TP + TN}{N} \tag{1}$$

- Precision: This is the ratio of true positive predictions to the total number of instances predicted to belong to a particular class. This is evaluated using "(2)."

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

- Recall: This is the ratio of correctly identified positive instances to the overall number of actual positives instances. "Equation (3)" denotes the recall.

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

- F1-score: This metric brings balance between precision and recall by calculating their harmonic mean.

- Sensitivity: Recall, also referred to as memory or sensitivity, represents the proportion of correctly identified positive Labels given by a model. It measures how well the model detects Positive cases, often given as a percentage. "Equation (4)" specifies the sensitivity.

$$Sensitivity = \frac{TP}{TP + FN} \tag{4}$$

- Specificity: This refers to the model's ability to correctly identify negative instances, showing how well it classifies negative labels. It can be evaluated using "(5)."

$$Specificity = \frac{TN}{TN + FP} \tag{5}$$

V. Result Analysis:

The "Performance Metrics" table is shown based on 22 classes of crop, ranging from 0 to 21. Class 0 represents barley, Class 1 corresponds to sorghum, and Class 2 denotes millet. The remaining samples are categorized as follows: 3—rye, 4—oats, 5—quinoa, 6—buckwheat, 7—amaranth, 8—spelt, 9—taro, 10—yam, 11—cassava, 12—sweet potato, 13—lentils, 14—soybeans, 15—flaxseed, 16—sesame, 17—groundnut, 18—sunflower, 19—mustard, 20—rapeseed, 21—sugarcane.

Table I shows confusion matrices for the new Graph Convolutional Network (GCN) compared to GNN, CNN and ANN baselines. The GCN has the highest correct classification rate and a significantly reduced misclassification rate compared to other models. The “Fig. 2.” indicates that the new proposed GCN outperforms the existing methods by both raise the classification accuracy and reduce error.

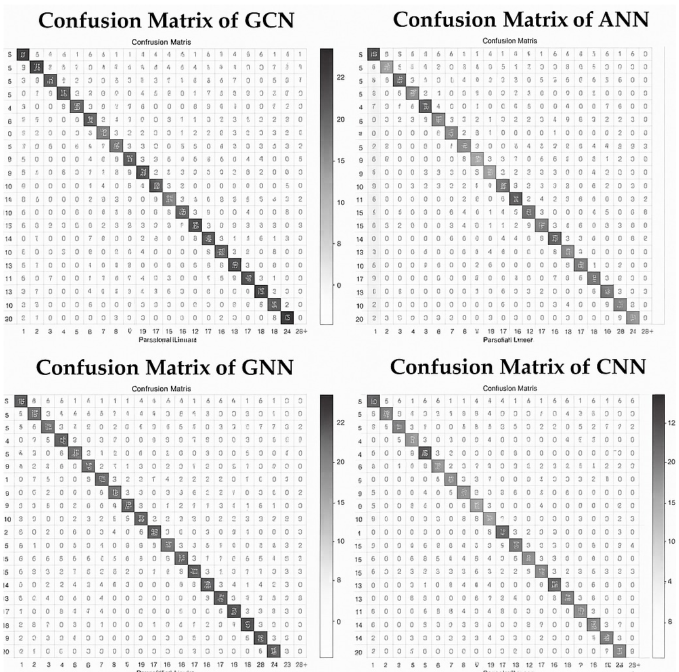

Fig. 2. Comparative Analysis of Proposed and Existing Methods

In addition, “Fig. 3” depicts a comparison of performance metrics, further emphasizing the effectiveness of the proposed method over conventional models.

Graph Convolutional Neural Networks are a better model for crop recommendation systems compared to traditional models precisely because they can effectively capture the complex relationships and dependencies between various agricultural factors. Traditional machine learning models typically consider every data point, for instance, a set of soil and climate parameters for a independent-it overlooks the essential fact that economic phenomena are linked with one another in time and space, i.e., at some specific location that influence crop yield and suitability.

Handling Interconnected Data: Unlike traditional models, GCNs are designed to work with graph-structured data. In a crop recommendation system, you can model different factors as nodes and their relationships as edges.

Nodes: can denote a particular location, type of soil, a weather pattern, or a crop.

Edges: Can model the relationships among them. like a place having a certain type of soil, the growth of a crop being affected by a certain range of temperatures, or under the influence of a given farm’s conditions.

By structuring the data this way, GCNs can perform graph convolution and feature aggregation, allowing them to learn from both the individual features of a node e.g., pH of the soil and the characteristics of its surrounding nodes, such as rainfall in a region nearby.

Improved Performance Indicators: Studies have showed that GCNs have consistently been cleared of high levels of performance parameters as compared to traditional machine learning models for crop recommendation tasks. This is because they can point out suitable patterns and relationships in the data that are overlooked by other models. GCN also finds a combination of soil nutrients, temperature, and humidity, along with the conditions in adjacent fields, that yield a suitable crop producing accurate and reliable recommendations.

Capturing Complex Dependencies: Identification of suitable crop is not examined by a single factor. GCNs are good at modeling such spatial dependencies. They can analyze how conditions in one factor (such as soil type, pest presence) may affect a neighbor field.

Spatial dependencies: They can inspect various conditions in one factor (soil type and pest presence) that affects a neighbor field.

Feature dependencies: These dependencies acknowledge how a high level of nitrogen interrelates with a particular pH level in the growth of a crop rather than isolated variables. These dependencies make GCN that is a powerful tool for precision agriculture where localized and dynamic decision-making becomes key to maximize crop production.

Fig. 3. Metric-Based Performance Evaluation

CONCLUSION

GCN-CRS enhances precision agriculture by making precise recommendations for crops based on agricultural and environmental data. The AI-powered approach improves yield and optimizes resource utilization to support environmentally viable farming. It also delivers data-driven decision-making tools for farmers to become more productive and responsive to global food security challenges. Results have shown that GCN-based Crop Recommendation Systems are far superior to the baseline machine learning algorithms such as ANN, CNN, and GNN with respect to the accuracy and trustworthiness of the crop recommendation. The system yields better performance indicators , therefore, proving the strength of its performance to capture the complex relationships among the feature vectors of soil characteristics, climate variables, and geographical dependencies. The research is a contribution to precision farming through enabling farmers to use intelligent decision-making tools and promises an encouraging solution to meet the challenges in global food security.

FUTURE WORKS

In future work, the recommendation system will be integrated with real time data that can be fetched from different IOT devices as well as satellite imagery for advancement of model's accuracy. The system for multiple crop cycles can be expanded with advanced deep learning techniques. For sustainable and profitable agriculture, it can also incorporate new market trends with effective economic factors that will optimize recommendations more accurately.

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