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Multimodal Deep Learning Framework for Crop Prediction Using Soil Image and Textual Feature with Convolutional Neural Network and Hybrid Convolutional Graphical Neural Network

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Abstract

Proper classification of soils is essential for the choice of appropriate crops and promoting agricultural productivity. In this work, Convolutional Neural Network (CNN) and Hybrid Convolutional Graphical Neural Network (HCGNN) models are compared for the classification of soil images, which is used to determine the best model to predict crop growth. The soil images were collected from Kaggle and were pre-processed into a dataset of 1156 images across 5 soil classes: Alluvial, Black, Clayey, Red, and Sandy before training a model. The CNN model takes off the visual features of the soil image, while the HCGNN transforms the convolutional feature abstraction with graph-based learning, and integrates the complex spatial relationships between the image features. From the experimental results, it is found that the HCGNN has a advanced accuracy of 97.50% on the test set compared with CNN with 87.41%. Based on the soil types predicted by the selected best performing model, appropriate crops are recommended which offers a reliable decision-support classification for precision of agriculture. The outcomes display that the graph-based deep learning has better classification accuracy and fewer misclassifications compared to the conventional CNN-based methods. This planned framework delivers an efficient and practical

solution for soil analysis and crop recommendations that can be implemented in automated systems and it could be used in smart farming and sustainable agricultural decision-making.

Keywords: Convolutional Neural Network, Hybrid Convolutional Graphical Neural Network, Classification, Crop recommend, Precision Agriculture.

1. Introduction

India is a leading farming country with around 58% of the population relying on agriculture and allied agricultural activities. Another important sector is agriculture which provides about 17% of India's GDP. A number of factors are involved in crop production, which are all interconnected, such as soil type, rainfall, sun, irrigation, use of fertilizer, pest control and proper land preparation. Hence, knowledge of these factors and their interactions is crucial to better yield in crops, the use of resources to their best advantage and for sustainable agriculture. **(Zambon et al. 2019; Bulent Tugrul et al., 2022)**. Agriculture plays a significant part in economic **(Calicioglu et al. 2019)** development and food security. The proper selection of the crop for different soil nutrients, climate, rainfall, temperature, humidity and pH is essential as traditional practices of crop selection based on experience is not sufficient to produce optimum crop output under varying environmental conditions **(Ayesha B. et al.2023)**. Because environment and soil factors play an imperative role in determining the yield of the crop, a focus is placed on the development of a crop management strategy that is appropriate to the site and soil **(Pruthviraj et al., 2020)**. Precision of agriculture has come a lengthy way in agriculture by improving irrigation systems, fertilizer management, suitable soil, and predicting crop yields **(A. Sharma et al., 2021)**. Today's farms and agriculture practices are conducted in many different ways than they were many decades ago, mostly because of the developments in technology, the use of sensors, devices, machines and knowledge technology in the agriculture sector **(Pradeepa B. et al. 2020)**. Smart farming is an important solution to the problems of productivity, environmental sustainability, food security, and efficient resource management that are faced by agriculture **(Gibbers et al.,2010).** As the global population raises, it is important to produce more food that is nutritionally adequate for a growing population and also conservation natural ecosystems through sustainable farming practices **(Kitzes et al., 2008)**.

Traditional crop recommender approach is mostly based on farmers experience, traditional knowledge and farming methods. The methods however may not always be reliable and timely in giving the recommendations, especially in the face of fluctuating climate and more variation in the environment. The advent of precision agriculture has brought new techniques in the field of machine learning (ML) and deep learning (DL) for crop prediction, disease detection, soil analysis,

and fertilizer recommendation. While these traditional models like Artificial Neural Networks (ANN), CNN, and other ML methodologies have shown potential performance, they are hard to formulate the complex and interconnected relationship among the various agricultural variables. The interdependency of factors like soil stuffs, climatic circumstances, crop features, and fertilizer requirements requires more advanced approaches that are able to effectively capture these relationships. **(Zhang et al., 2021)**. A sensor based environmental monitoring, machine learning grounded crop recommendation system for better farming decisions. Multiple agricultural parameters are analyzed and crops with high accuracy are recommended by the system. In addition, a farmer feedback mechanism is included to continuously enhance the accuracy of prediction, that is, the system is more reliable, efficient and practicable for modern agriculture **(Bandara P et al. 2020)**.

A promising approach is to represent image regions as the nodes of a graph and learn spatial relationships by passing messages between the nodes of the graph, called Graph Neural Networks (GNNs). This research introduces a CNN-HCGNN architecture for the classification of infrastructure based on satellite images occupied from the Kaggle dataset. The proposed model is designed to decrease the classification error by incorporating CNN-based feature extraction and HCGNN-based spatial reasoning **(Senapaty,M et al. 2024).**

In this research, two ML models are used to classify soil types from soil images: CNN and HCGNN model. The performance of the two models is checked with respect to classification accuracy. The superlative model is the one that has the uppermost accuracy. On the basis of the soil type, at least two crops that are suitable for growing are recommended. This offers farmers information about what crops to plant and improves farming output.

The work is distributed into the following sections: Literature Survey – literature pertaining to past research on soil classification and crop recommendation. The Methodology section explains the proposed system and implementation of CNN and HCGNN in detail. Results of the performance comparison and the crop recommendation results are presented in the Results section. Finally, the outcomes are summarized in Conclusion and references are provided that are used in the research.

1.1 Objective

This study aims to create a practical and effective solution to classify soil and recommend the most suitable crop for each type by implementing a Hybrid Convolutional Graph Neural Network (HCGNN). The objective of the study is to precisely classify the soil types based on soil images using a CNN that has a feature-learning ability and a GNN that has a relational learning ability. The system will suggest appropriate crops for a particular soil condition based on the category of soil

identified and its properties. The other goal is to better the performance of the crop recommendation and gain accuracy over traditional machine-learning methods and conventional CNN-based methods. Another key aspect of the study is to build a lightweight and computation-efficient HCGNN model that can achieve high performance even on a small scale of soil images. Finally, the suggested framework is designed to be a viable, effective, and usable approach that can assist farmers and farmers' practitioners in selecting better crops for future precision-agriculture applications.

2. Literature Review

Khaki et al. (2020) developed a DL model with a hybrid CNN and Recurrent Neural Network (RNN) to enhance crop yield forecasting. The CNN captures spatial and temporal structures from climate and soil data, and the RNN with LSTM captures long-term weather trends and annual yield patterns. The projected model was assessed using corn and soybean data from 13 states in the U.S. Corn Belt, yielding better RMSE results than Random Forest, DFNN, and LASSO models. The researchers also developed feature importance analysis to determine weather, soil, and management factors that affect yield prediction. This research displays the potential of CNN-RNN models for yield prediction.

M. Rashid et al. (2021) gave a comprehensive review on ML and DL procedures to forecast crop yield with highlighting on palm oil yield prediction. Following the PRISMA methodology, 223 research studies were analyzed and significant agricultural parameters such as weather, soil properties, irrigation, vegetation indices, satellite data and historical crop yields were identified. The study focused on comparing the performance of conventional ML models with advanced DL models like CNN, LSTM, CNN-RNN, and CNN-LSTM. It was found that hybrid deep learning models usually performed well in prediction as they can capture both spatial and temporal relationships in agricultural data. The authors raised some issues such as data standardization, feature selection, and few studies dedicated to palm oil specifically. They proposed to combine IoT, wireless sensor networks, and high-resolution remote sensing information for further enhancing crop yield prediction.

A. Eskadarinia et al. (2010) assess the forecasting ability of two data-driven approaches: ANN and K-Nearest Neighbor (KNN) for daily flow prediction. ANN is well known for capturing nonlinear dependencies among hydrological variables, and KNN is a straightforward non-parametric method which estimates the output values based on similarity to past data. The researchers compare the performance of the two techniques on historical daily flow data using Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and correlation coefficient. The conclusions suggest that ANN tends to offer better prediction performance and generalization performance thanks to its

capability to capture nonlinear relationships in time series. But KNN is also highly performant with reduced computational cost and simplicity. The authors conclude that ANN is a better choice for complex hydrologic forecasting, but KNN is a viable alternative for simpler forecasting problems or small datasets.

Shahhosseini et al. (2021) developed two ensemble DL approaches based on CNNs and Deep Neural Networks (DNNs) for large-scale corn yield prediction in the U.S. Corn Belt. The study used historical yield, weather, soil, and management data collected from 1980 to 2019. Two one-dimensional CNNs were designed to extract spatial and temporal patterns from soil and weather variables, while fully connected DNN layers were used for yield prediction. The researchers further developed homogeneous ensembles using bagging and heterogeneous ensembles using different hyperparameter settings. These models were combined using the Basic Ensemble Method (BEM), Generalized Ensemble Method (GEM), and stacking techniques. The ensemble CNN-DNN models outperformed conventional machine learning methods, including Linear Regression, LASSO, Random Forest (RF), XGBoost, and LightGBM, as well as previously developed CNN-RNN models. The homogeneous ensemble achieved the best performance, with an RMSE of 866 kg/ha and an ability to explain 77% of the spatial-temporal variation in corn yield, demonstrating strong generalization and robustness for large-scale crop yield prediction.

Kiran Sree Pokkuluri et al. (2022) suggested a new framework combining CNN and Cellular Automata (CA) to predict crop diseases and yield. The paper presented two classifiers, CNN-CA-I to detect disease using the image and CNN-CA-W to predict disease based on the weather condition. The image-based model was trained on a huge collection of crop leaf images comprising 245 crop species and 132 diseases with an accuracy of 92.6% of the total prediction. The weather-based classifier used environmental parameters including temperature, humidity, rainfall, atmospheric pressure and wind speed, which is based on ECMWF datasets with a reported accuracy of 90.1%.

Cellular Automata integration enhanced the extraction of features, image segmentation and classification efficiency by enhancing CNN filters and optimizing the spatial pattern recognition. In contrast to other previous studies, which employed the method of leaf image analysis or weather forecasting, but not both, this study combined both the two approaches in order to improve the reliability of disease prediction. The proposed framework proved to be efficient in computing with prediction time less than 0.5 nanoseconds and thus it is applicable in real-time agricultural conclusion support. The paper has illuminated the promise of hybrid DL systems in smart agriculture systems to accurately diagnose crop diseases and predict yields.

The authors Thomas van Klompenburg et al. (2020) systematically reviewed 50 studies related to crop yield prediction from an initial sample of 567 studies retrieved from six electronic databases. ANN was found to be widely used due to its good modeling capacity of complex and nonlinear relationships between the agricultural variables. Prediction variables used were temperature, rainfall, soil type, crop management, and fertilizer application, and humidity. The authors have also reviewed 30 literature about deep learning and reported that CNN, LSTM networks, and DNNs were among the most popular used DL methods to boost the accuracy of prediction. The results also suggested that the incorporation of climatic data, soil data, and remote sensing data can greatly improve model performance. But there are still problems of data quality, feature selection and generalizing the model across geographical regions. Overall, the study is a solid basis for the creation of intelligent crop yield forecasting and decision-support systems for sustainable agriculture.

To detect soybean leaf disease, Md Abrar Jahin et al. (2025) combined MobileNetV2 with GraphSAGE to achieve better performance. The model utilizes CNN to extract the features of each image, and applies GNN to learn relationships between similar leaf images. Leaf image in soybean are mapped as nodes, and the cosine similarity is mapped by means of the connection between leaf images. The model was evaluated on 10 leaf diseases of soybeans, with a 97.16% accuracy rate, surpassing other traditional methods such as SVM, RF and LR. To be more interpretable and trustworthy for agriculture, important disease areas were emphasized using Grad-CAM and Eigen-CAM.

Saeed Khaki et al.(2020) projected that CNN-RNN model used to capture weather patterns, historical yield dependencies and soil characteristics using hybrid CNN-RNN model. Their model was good for preidicting corn and soyabean than RF, LASSO, and Deep fully connected neural network. It is also introduced feature importance analysis, which improved the interpretability of the model and proved that a deep learning model can effectively predict crop yields.

Dr. Mahaveerakannan R et al (2025) suggested a hybrid quantum DL based approach for predicting rice yield using optical remote sensing, UAV multispectral imaging and weather data. They also suggested that integrated quantum computing with deep learning to determine complex datasets from the agriculture industry and enhance prediction accuracy. The designed model has been compared with conventional ML techniques and traditional DL techniques. The experimental consequences indicated that the hybrid model was found to be more accurate, less error rates and more reliable for rice yield prediction. The work highlights the opportunity to leverage cutting-edge computation techniques and remote sensing in precision farming and food security.

Joshua Fan et al. (2022) planned a hybrid model of GNN-RNN for the prediction of crop yields. Weather, soil, and land surface data from more than 2,000 counties from 1981 to 2019 is used in the model. Spatial relationships with the closest counties were modeled using GNN and temporal yield dependencies and historical trends were modeled using RNN. The framework was evaluated using experiments conducted with the crop yields of corn and soybean, and it displayed improved performance when compared to the traditional ML models, as well as current DL techniques, demonstrating the power of geospatial and temporal data in agriculture.

Zhengtao Li et al. (2020) projected a CNN-Transformer crop classification model on multiple time and date Sentinel-2 and Landsat-8 satellite images. This model used CNN to extract the important spatial features and the Transformer to extract the temporal features from the crop data. The outcomes showed that the projected model was outperforming the existing models like CNN, CNN-LSTM, SVM and Random Forest. It was able to determine other crop types, achieve higher classification accuracy, even for crops with similar growth patterns, indicating the potential of DL in the field of crop monitoring and precision agriculture.

K. Ananthajothi et al. (2026) suggested a hybrid approach of Gabor-GNN model for plant leaf disease classification by utilizing image processing and DL methods. The model used Gabor filters to identify significant texture features like spots, edges and irregular disease patterns in leaf images, and the Graph Neural Networks captured the spatial and structural relationships between diseased areas. This model was trained on Plant Village and tested 98.4% and 94.6% accuracy compared to the standard GNN model. The study showed that the proposed approach proved to be effective for precision agriculture in noise and low contrast environment.

To overcome this challenge, U. Nirosha et al. (2025) projected a crop yield prediction model using Federated Learning (FL) in conjunction with an Attention-based Graph Neural Network (AGNN) and RNN. The model used the Agricultural data from various States of India, such as Rainfall, fertilizer utilization, pesticide utilization, area of crop cultivation, and production of crops. With federated learning, distributed models were trained while keeping the data private, which gave the opportunity to use data from multiple sources to train the model without having to send the underlying data sets. The experimental consequences displayed that the accuracy of the prediction was high, where the MAE was low, RMSE was low, the correlation was high, and the R^2 value was high, which amounted to 95.50%. The proposed FL-AGRN model was also found to be better in terms of crop yield prediction than the conventional ML and DL approaches. The study outlines the possibilities of hybrid models of graph-based learning, recurrent networks, and privacy-preserving federated learning in creating scalable and intelligent agricultural prediction systems.

A. Haridasan et al. (2023) have suggested about detection of paddy plant diseases using image processing, ML and DL technique. Pre-processing, Segmentation, Feature extraction, PCA, SVM, and CNN are the methods used for identifying the disease including brown spot, leaf blast, sheath rot, false smut and bacterial blight. Image augmentation and feature optimization allow for enhanced accuracy and reduced processing time. In these approaches, CNN-based models outperform the traditional manual disease detection approach. These technologies are used for precision agriculture where they can help detect the occurrence of disease early, minimize the utilization of pesticides, monitor crops and enhance rice productivity in sustainable agriculture.

K. S. Saravanan et al. (2024) suggested a ML and DL models for estimating the yield of crops in India based on agricultural data from the period 1997-2017. To boost the accuracy of the prediction, the CatBoost model and the STACNN-BiLSTM model were applied to the study. It was found that both models are accurate in predicting yield of crops with very small error. The CatBoost model slightly outperformed the others with an R2 value of 0.99. The models projected in this study were more successful than traditional techniques and contributed to the progress of precision agriculture, crop planning, and decision making for farmers and agricultural professionals.

D. R. I. M. Setiadi et al. (2024) presented a hybrid model, namely Quantum DL, which is composed of BiLSTM, quantum feature processing and XGBoost techniques to predict the yield of rice from agricultural information from 67 countries. The study indicated that the combined technologies of quantum computing and deep learning improve the representation and prediction of features. The experimental results obtained better MSE and MAE values and high R^2 value of 0.99993 as compared to traditional ML and DL approaches. The projected model was successful for the precision agriculture, crop forecasting and decision making in agriculture.

S. Vijayan (2025) designed and implemented a smart, CNN-based disease detection model for rice crop using image processing and feature optimization techniques. Pre-processing, Segmentation, Feature Extraction, and the Hybrid WOA_APSO optimization algorithm were employed in the study for the identification of diseases such as Brown Spot, Hispa, Leaf Blast from PlantVillage data. The accuracy of the proposed model was 97.5%, which is better than the ANN, SVM and normal CNN model. It also reduced the computing time and improved feature selection, that can be extended to precision agriculture and early diagnosis of crop diseases.

With the participation of soil-climate-agricultural data, Q. Zhang et al. (2022) suggested using GNN to help decision-making on crop variety selection. The model tested environmental conditions to crop characteristics to see if this more accurately represents the crop selected. The GNN model showed significant improvement over the conventional machine learning techniques when

predicting the appropriate crops. The research demonstrated how graph-based learning can efficiently integrate large-scale agro-related data to empower their use by farmers in decision making with regard to their crop selection, production optimization, and support precision agriculture and informed farming choices.

Through the proposed models by Youngho Min et al. (2025), the authors tried two models, namely RNN and GNN, with the aim of predicting the agricultural commodity prices based on the multivariate time series data such as wholesale prices, weather data, and seasonal data from South Korea. To enhance the accuracy of price forecasting, stacked LSTM, StemGNN and Temporal Graph Convolutional Network models were used in the study. The experimental outcomes specified that the models using GNN outperformed the models based on RNN in terms of agricultural prices prediction and short-term price fluctuations reduction. The suggested strategy successfully captured relationships between several variables, which helps in good agricultural prices forecasting and decision-making for markets.

In order to effectively classify images, the authors in this paper, Fei et al. (2023), designed an end-to-end GNN architecture comprising of both local CNN-based feature extraction and global-attention GCN-based learning. They proposed a novel approach called Global Multi-head Self-Attention Pooling (GMSAPool) that can capture key global node relationships while avoiding the need to preprocess the graph in the previous process. The model was found to be more effective than previous CNN and GNN baseline models on Agricultural Disease, Caltech256 and CIFAR-100 datasets. This work shows that combining local and global-attention features can greatly improve the classification accuracy on various image datasets.

2.1. Research Gap

While a few studies have compared CNN and hybrid CNN–GNN models are recently done, they have mainly addressed the task of plant, vegetation or general image classification, instead of soil-type classification. For instance, CNN-GNN integration has been demonstrated in recent works to be effective for combining visual and relational information and enhance classification performance. But the capabilities of HCGNN to classify soil classes with similar characteristics from visual images are yet to be thoroughly investigated, especially with small soil-image datasets containing multiple classes. The viability of graph-based relational learning in discriminating classes is also limited evaluated against CNN and hybrid quantum models. To meet this requirement, this study aims to develop and evaluate HCGNN for soil classification systematically and compare it to the existing approaches.

2.2 Contribution

- Compares the performance of CNN with the proposed HCGNN for soil image classification.
- The classification reports were created for models and included precision, recall, F1-score and accuracy.
- The experimental consequences demonstrated that the HCGNN outperforms the CNN in terms of classification accuracy. This means that HCGNN has the ability to learn more meaningful relationships and features from the soil images, resulting in better soil type recognition.
- Combination of soil image information and text-based agricultural information in the HCGNN model. This multi-modal approach can give more valuable information than soil image approach itself.
- After combining image and text/tabular information, the HCGNN model was used to predict suitable crops

3. Proposed Work

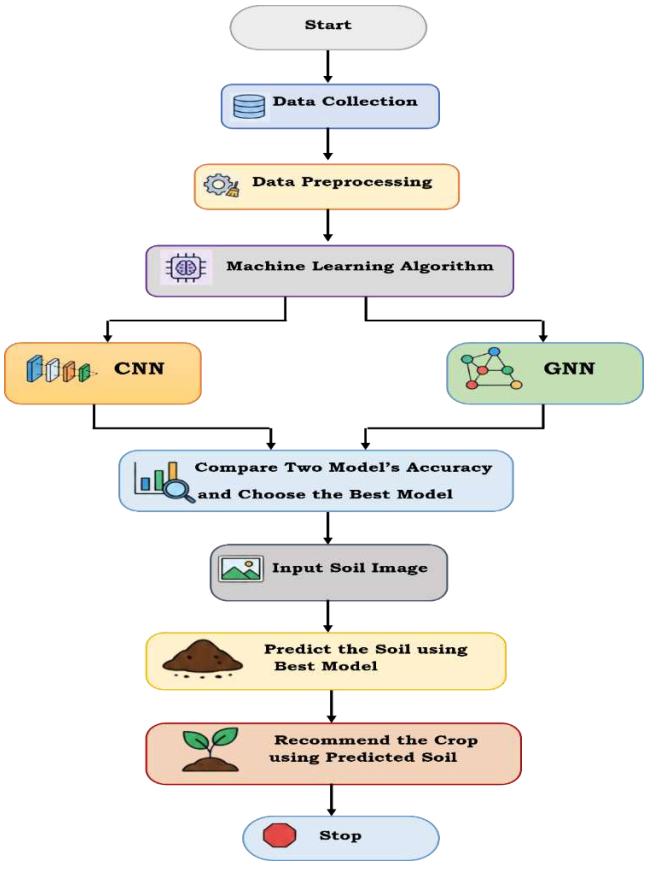


Fig.1 Proposed framework

Initially, data was gathered from a Kaggle website of 1000 samples, which has four soil types: red, alluvial, clayey and sandy. The data was then preprocessed. Two machine learning models, CNN and Hybrid CGNN, were used and compared to find the top model with the highest accuracy. Then, an image of soil was given to the system, the type of soil was predicted using the best model, and finally, yields that can be grown on the soil were suggested. Fig. 1 shown the overall workflow of proposed framework.

3.1 Data Collection (Image, Text)

Table.1 Data Split Information

Dataset Category	Number of Images	F1-Score
Training Images	809	69.98%
Validation Images	173	14.97%
Testing Images	174	15.05%
Total Images	**1,156**	**100%**

Table.2 Soil Class Distribution

Sl No.	Soil Class	Number of Images
1	Alluvial	250
2	Black	228
3	Clayey	188
4	Red	262
5	Sandy	228
	Total Images	**1,156**

The data is obtained from the Kaggle website, and consists of 1156 images of various soil types. These soil images are available in five different categories: Alluvial soil (250 images), Black soil (228 images), Clayey soil (188 images), Red soil (262 images) and Sandy soil (228 images) as shown in Table.2. These classes help the model to differentiate between the various soil classes and classify them accurately.

After the data set was assembled, the images are divided into three sets for use with the machine learning algorithms. The first set consists of training images (809 images). The set is used for training the model and it will get to know the properties of soils. The other one is the validation set, consisting of 173 images which are utilized to evaluate the model's performance during training process to fine-tune the model. The third is the testing set comprising of 174 images as shown in Table.1.

```
--- Dataset Info ---
              N           P           K  temperature   humidity        pH  \
0     52.435617   80.601668  148.747924    13.362129  64.216311  4.054141
1    133.100003  128.211072  151.480210    17.929871  29.179357  7.391376
2    102.479152   96.122832  107.986670    24.107044  30.091013  3.671462
3     83.812188   79.614090   37.272560    33.486098  62.362689  8.286082
4     21.842610   50.406725   21.710868    31.663015  41.508924  4.262589
...         ...         ...         ...          ...        ...       ...
1604   9.719338  102.152943   80.410786    38.120926  98.378747  4.603390
1605  72.668371   37.143743   83.664134    36.212331  41.462082  5.080317
1606   9.465759   21.457182  113.911065    24.486151  23.278258  4.390426
1607 112.049911   28.139829   36.975953    32.788884  76.405063  4.871124
1608  32.719691    5.278899  143.249333    25.988632  56.078920  4.736877

        rainfall        label   Soil Type
0     191.418100         jute    Red Soil
1     205.687289  kidneybeans    Red Soil
2     331.832649         rice  Black Soil
3      84.538314   groundnuts    Red Soil
4     231.752984       lentil      Clayey
...          ...          ...         ...
1604  315.613623       cotton    Alluvial
1605  110.630170   watermelon  Black Soil
1606  110.116879  kidneybeans      Clayey
1607  119.865354       celery      Clayey
1608  222.063417  kidneybeans      Clayey

[1609 rows x 9 columns]
```

Fig.2 Text Dataset

The Fig.2 shown text data set used for crop type analysis. The dataset has 1,609 rows of data and 9 columns containing important agricultural and environmental characteristics. The input variables are commonly known and known to be important to crop growth and soil properties: Nitrogen (N), Phosphorus (P), Potassium (K), temperature, humidity, pH and rainfall. There are also two categorical variables in the dataset: label, the recommended crop (e.g., jute, rice, kidney beans, groundnuts, lentil, cotton, watermelon, celery), and Soil Type (e.g., Red Soil, Black Soil, Clayey, Alluvial). The nutrient data and climate data shown are fairly variable, reflecting diverse agricultural settings. This diversity can be useful in creating strong machine learning models that can identify complex interactions among environmental conditions, soil types and crop suitability. The dataset is suitable for predictive modelling applications such as soil classification, crop recommendation, and precision agriculture applications, because there is no apparent inconsistencies in the sample records, and the numerical and categorical features are well balanced.

3.2 Data Preprocessing (Image)

The soil image data set contains 1,156 soil images which are categorized according to five soil classes: Alluvial (250), Black (228), Clayey (188), Red (262), Sandy (228). Image pre-processing was achieved to progress the quality of image and uniformity before training the DL models. All images were resized to the common dimension that is suitable for CNN-based models and converted to a common image format. To make the model converge and have a stable training process, the pixel values were standardized to a proper range. Images can be augmented using methods such as rotation, horizontal flipping, zooming and shifting to make them more varied and less prone to overfitting. The dataset was divided into 809 training images (69.98%), 173 validation images (14.97%), and 174 testing images (15.05%). The training set was employed in the model learning, the validation set was employed in the tuning of the parameters and the testing set was employed to evaluate the final model's generalization performance.

3.3 Data Preprocessing (Text)

The data comprises 1,609 samples from 9 variables including soil nutrients (N, P, K), environment variables (Temperature, Humidity, pH, Rainfall), and categorical variables (Crop label and Soil type). The numerical features were analyzed for missing and inconsistent values during the preprocessing phase, and then mapped to appropriate numerical formats. The crop label and soil type are categorical data types, so they were converted to numerical data types for machine learning models. The numerical features were also checked for outlying and scale effects. If needed, feature scaling or normalization can be used to normalize the numerical values of features, so that the numerical range of each feature is the same. The cleaned and transformed data was then ready for training and testing of the model. This pre-processing ensures data quality, model stability and the prediction accuracy of the crop and soil-based prediction.

3.4 Model Trained

3.4.1 HCGNN (Hybrid Convolutional Graphical Neural Network)

The Hybrid Convolutional Graphical Neural Network is a fusion of two strong deep learning paradigms: CNNs and GNNs that can be used to process data that has a local arrangement (e.g., images, spatial data) as well as a relational/topological structure (e.g., graphs, networks). Each architecture is good at a specific type of thing, so using them together lets you get a pattern that neither could get by itself.

Why Agriculture needs a Hybrid Approach.

The data from agriculture is naturally multimodal, that is, it involves also spatial information, relational information, which cannot be easily represented by a single model. CNNs work well with grid-based data like satellite images, drone images, soil moisture maps, temperature data, rainfall

data and vegetation indices like NDVI and NDWI. They can identify key spatial patterns of soil texture, erosion, moisture stress, vegetation health and land-cover change. GNNs are useful for soil nutrient relationships (N, P, K, etc.), for soil and neighbors in farm plots, for crop rotation, and for the interactions among soil and climate and soil and crop characteristics, however. By employing a hybrid CNN-GNN framework, these advantages are combined by first capturing important spatial features by CNN layers and then learning the relationship among various regions or agricultural parameters by GNNs. The joint learning can yield more accurate and informative prediction than either CNNs or traditional regression models alone.

3.4.2 Conventional Neural Network

CNNs are traditional classical ML procedures which are widely used in image and computer vision problems. They employ convolutional layers with small filters (2×2, 3×3) to extract relevant features from images and with pooling layers to compress the amount and keep relevant information. Next, there are completely connected layers for output.

In 2018, Cong Iris et al. presented a model that is based on CNNs called Quantum Convolutional Neural Network (QCNN). QCNNs use quantum circuits as opposed to classical layers that perform similar operations, with quantum gates acting as filters to extract key features from quantum data and reduce its size. The Fig. 4 illustrated the CNN layer.

3.4.3 How does CNN work?

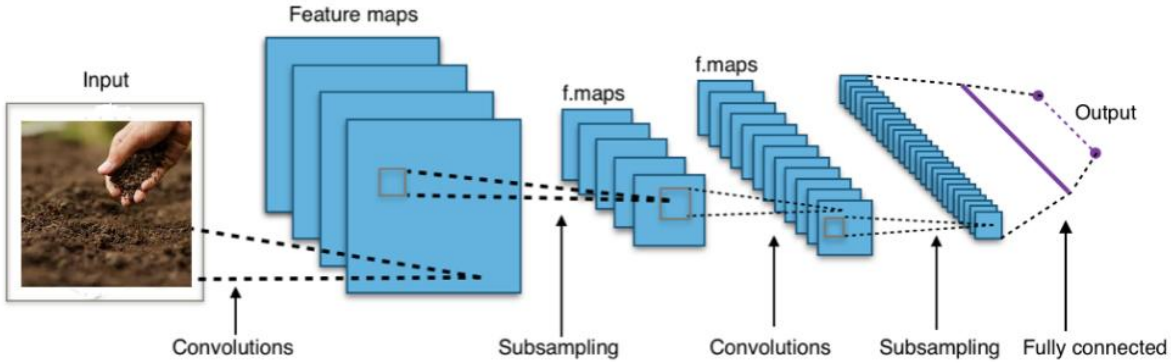


Fig.3 CNN Layers

A CNN is made up of convolutional and pooling layers. The convolutional layers learn features of the image and pooling layers down sample the data. Then the output is fed to fully connected layers for classification.

3.4.3 Stages on CNN operations

3.4.3.1 Convolutional Layer

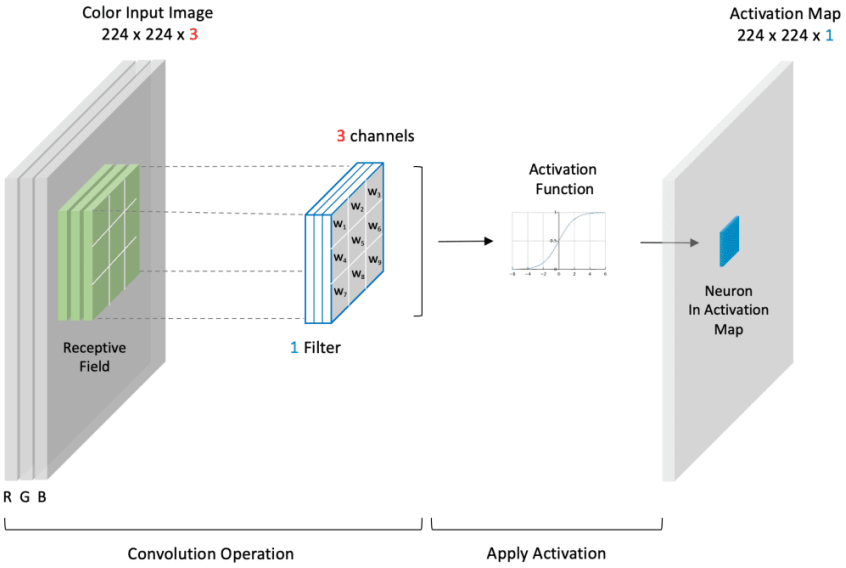


Fig. 4 Convolutional Layer

Input Image (Left side): Image of size 224 * 224 * 3 (3 is the number of channels, which are Blue, Green and Red). Receptive Field: Small area of image is selected. The area of the image that the filter is now concentrating on. Kernel: A kernel with weights (W1,W2....Wn) goes through the image. The depth of the filter is = 3 because there are 3 channels in the image. This filter can be used to recognize edges, texture, patterns. Convolution Operation: The filter takes individual points within the receptive field and multiplies them by the value contained in the filter, then adds up the totals to get one value. The Fig. 4 displayed the convolutional layer.

3.4.3.2 Activation Function

The number passes through an activation function (e.g. ReLU) which adds non-linearity. Activation Map (Right side): This is a feature map (224 × 224 × 1). The values are a measure of the strength of the feature detected at that point. Neuron Representation: An activation map is a map of a neuron detecting a feature.

3.4.3.3 Activation Layer

The Activation Layer is an added power to the network. This enables the model to learn humanly by making the output of the convolution layer non-linear. This is done by using a simple activation function on each part of the output. It allows the model to be trained in patterns other than straight lines. The size of the output for example 32 × 32 × 12 stays the same. **Pooling Layer**

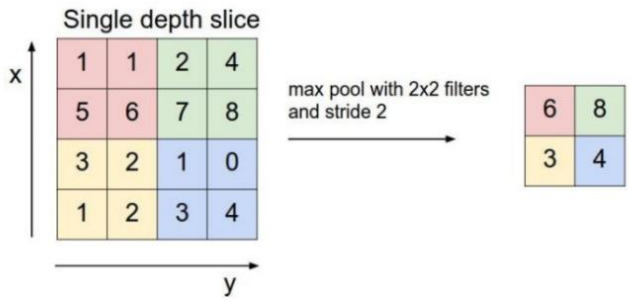


Fig.5 Activation Layer

The Pooling Layer is utilized to minimize the spatial size of the feature maps, which makes computation faster and reduces memory usage to prevent overfitting. It is typically placed between the convolutional layers of a CNN. The Fig. 5 shown the activation layer of CNN model.

3.4.3.4 Flattening

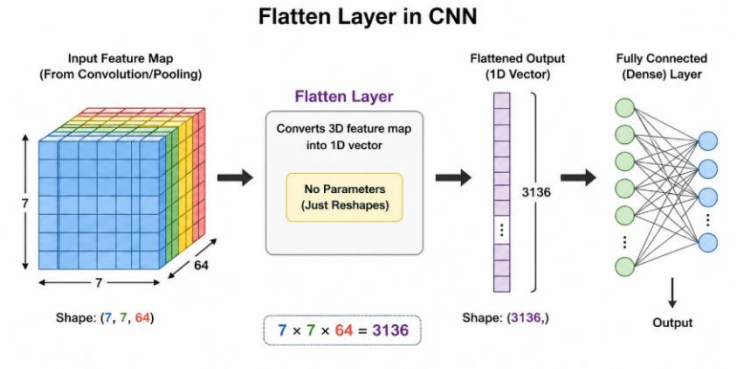


Fig.6 Flatten Layer in CNN

It transforms multi-dimensional feature maps from the convolution and pooling layers into a one-dimensional vector. This step is necessary because dense layers require 1D input. The Flatten layer reshapes the data, it does not learn or change values. Fig. 6 shown the flatten layer of CNN model.

3.5 Graphical Neural Network

The Graphical Neural Network (GNN) was specially designed to efficiently handle graph-structured data. Convolutional DL models work on Euclidean data spaces (such as images and grids), whereas GNNs are designed for non-Euclidean data spaces (where relationships between entities are expressed as graphs).

A graph is formally represented as:

$$G = (V, E, X_V, X_E) \quad (1)$$

where

$V = \{v_1, v_2, \ldots, v_n\}$signifies the set of nodes (vertices), with $n$total nodes.

$E = \{(i,j) \mid v_i \text{ is connected to } v_j\}$represents the set of edges.

$X_V = \{x_1, x_2, \ldots, x_n\}$denotes node feature vectors, where $x_i \in \mathbb{R}^d$is the feature symbol of node v_i.

$X_E = \{x_{(i,j)} \mid (i,j) \in E\}$represents edge feature vectors, where $x_{(i,j)}$encodes information associated with edge (i,j).

In GNNs, each node maintains a hidden state vector that evolves over time through message passing. The graph at time step $t$is represented as:

$$G_t = (V, E, X_V, X_E, H_t) \tag{2}$$

where:

$$H_t = \left\{h_1^{(t)}, h_2^{(t)}, \ldots, h_n^{(t)}\right\} \tag{3}$$

It is the collection of concealed state vectors of all nodes at iteration t, and $h_i^{(t)} \in \mathbb{R}^m$denotes the concealed representation of node v_i.

The concealed state update rule is defined as:

$$h_i^{(t)} = f_w\left(x_i, x_{co(i)}, h_{ne(i)}^{(t-1)}, x_{ne(i)}\right) \tag{4}$$

where:

$f_w(\cdot)$is a learnable transformation function parameterized by weights w,

$x_i$is the feature vector of node v_i,

$x_{ne(i)}$represents features of neighboring nodes,

$x_{co(i)}$represents features of edges connected to node v_i,

$h_{ne(i)}^{(t-1)}$signifies concealed states of adjacent nodes from the previous iteration.

A common aggregation operation is:

$$m_i^{(t)} = \sum_{j \in N(i)} W_m \, h_j^{(t-1)} \tag{5}$$

followed by node state update:

$$h_i^{(t)} = \sigma\left(W_h x_i + m_i^{(t)} + b\right) \tag{6}$$

where $N(i)$denotes neighbors of node i, $W_m$and $W_h$are learnable weight matrices, $b$is bias, and $\sigma(\cdot)$is an activation function such as ReLU.

After Titerations, the final node embedding is:

$$z_i = h_i^{(T)} \tag{7}$$

Then the embeddings are applied in the downstream tasks like node classification, graph classification and link prediction. This neighborhood aggregation process is performed iteratively, which allows GNNs to successfully learn both node attributes and graph structure.

4 Result Analysis

4.1 Convolutional Neural Network

4.1.1 Train accuracy Graph

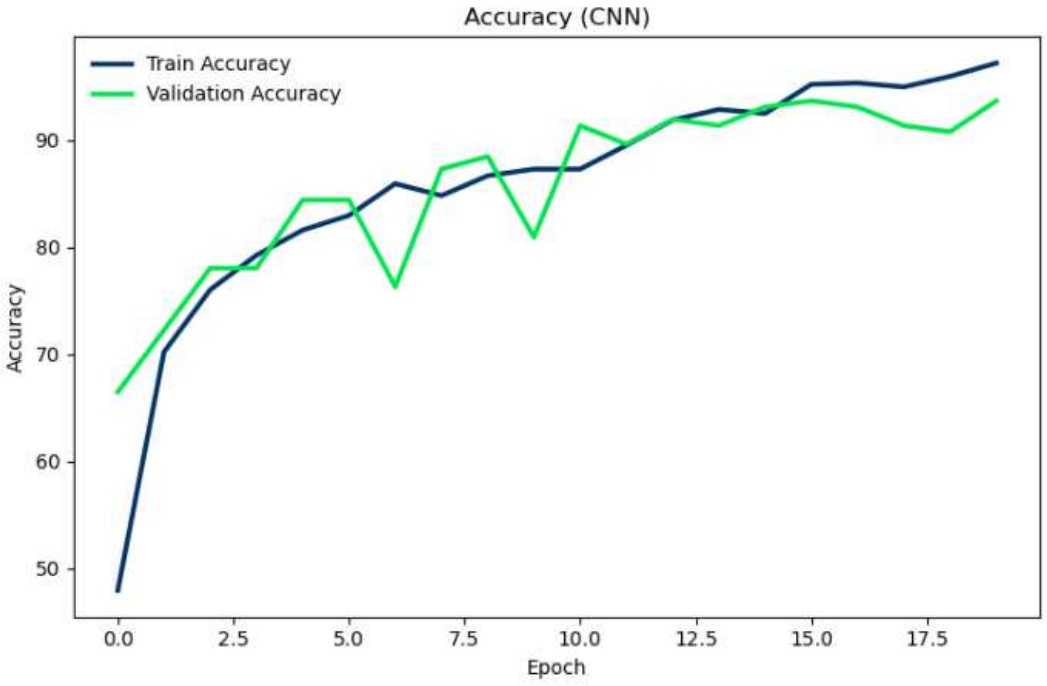


Fig.7 Train Accuracy and Validation Accuracy of CNN

The above Fig.7 show the accuracy graph of CNN trained for 20 epochs and validated. The accuracy in training begins at approximately 48% and gradually rises until the end of the epoch at around 97%. The accuracy on the validation data is also increased, from ~67% to ~94%, though there are some fluctuations during training. During the mid-periods, the accuracy of validation occasionally decreases but recovers and continues to improve. Training and validation curves are kept close together for most epochs, suggesting that the model is not overfitting. The CNN's accuracy reaches high levels on the training and validation sets at the end of training. In general, the graph shows that the CNN model has acquired valuable features and performs well and consistently on the classification task.

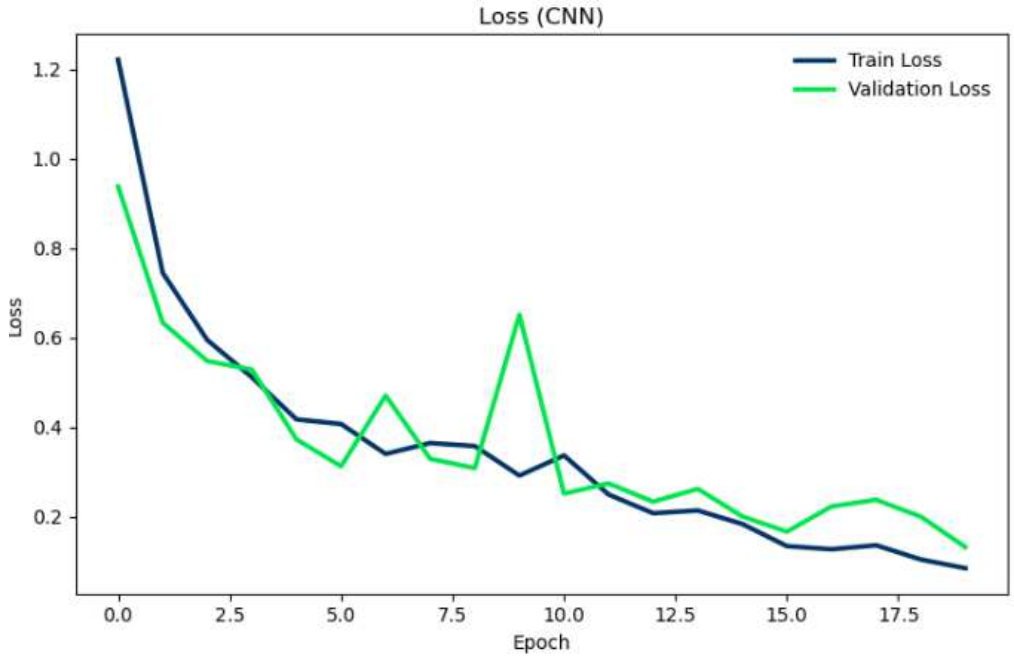


Fig.8 Train and Validation Loss of CNN

The Fig.8 depicts the training loss and validation loss values of the CNN model for 20 epochs. The initial training loss is 1.22 and the initial validation loss is 0.94. The losses are extremely low in the early epochs, indicating the model is learning well. The validation loss rises at some places, e.g. in the middle of training, but is generally decreasing. At the end of the epoch, the training loss will be around 0.08, and the validation loss will be around 0.14. As the loss values continue to decrease, the CNN is continuously improving its predictions and minimizing errors. The similarity of training vs validation loss is also a noble indicator that the model is generalizing fairly well to unseen data. Overall, the graph shows stable learning and a good convergence of the CNN model while training.

4.1.2 Test Accuracy

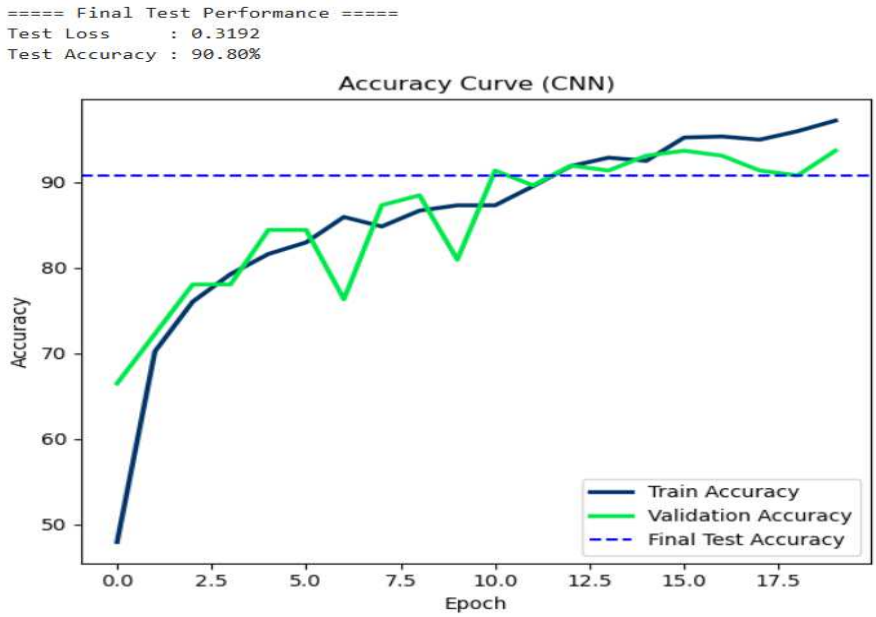


Fig. 9 Final Test Accuracy of CNN model

The CNN model is evaluated for 20 epochs and the performance is presented in the Fig. 9. The model's accuracy continues to rise during training and validation, indicating good learning from the data. The training accuracy increases from approximately 45% to 96% and the validation accuracy is about 92%. Validation curve is close to the training curve and has minor fluctuations which indicate that the model does not overfit significantly. Both curves tend to level off at about 90% after the 10th epoch. The final test accuracy is 90.80% with a low-test loss of 0.3192, indicating that the CNN model gives less accurate and reliable results on the test dataset. Training loss and validation loss are seen to be reducing monotonically with the number of epochs, signifying that the model is learning well over time.

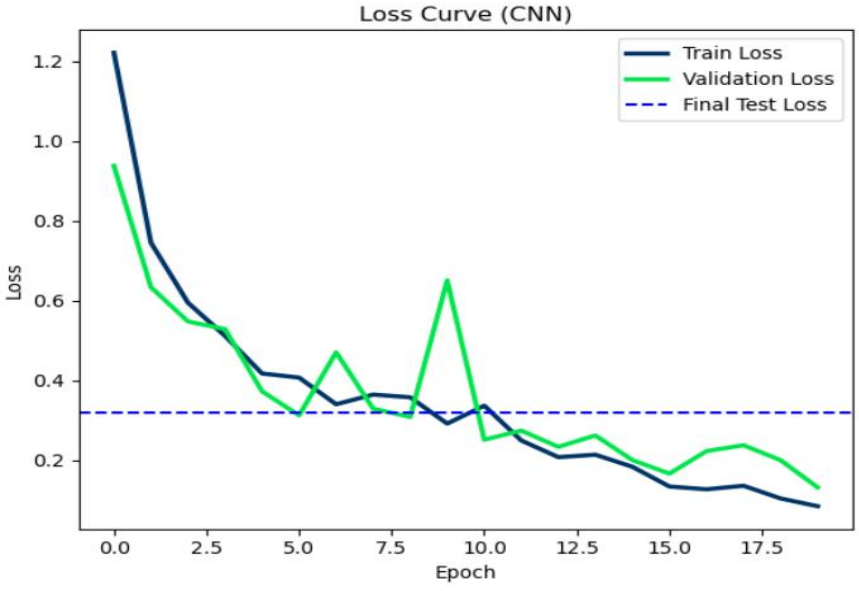


Fig. 10 Final Test Loss of CNN model

Both the total loss for training and validation sets are decreases, indicating good learning and prediction performance. The training loss gradually decreases from approximately 1.22 during the first epoch to almost 0.08 during the last epoch, indicating good convergence. The validation loss also improves, from approximately 0.94 to 0.13, however, it is not entirely stable at some points, such as between epoch 8 and epoch 9 where a peak is seen. These fluctuations are still, however, downward, indicating good generalization performance. The loss on the final test set is around 0.32, showing good performance on test. Overall, the Fig.10 shows with minimal over-fitting and good model accuracy.

4.1.3 Classification Report

Table.3 Classfication report of CNN model

Soil Type	Precision	Recall	F1-Score
Alluvial	0.91	0.78	0.84
Black	0.93	0.95	0.94
Clayey	0.77	0.87	0.82
Red	0.94	0.97	0.95
Sandy	1.00	1.00	1.00
Accuracy	—	—	**0.91**
Macro Average	**0.91**	**0.91**	**0.91**
Weighted Average	**0.91**	**0.91**	**0.91**

The classification report of CNN is 91% with 174 test samples indicating that CNN performs well on five soil classes as shown in Table 1. In the end, the model produces high accuracy, with the F1-scores for Red, Black, and Alluvial soil classes of 0.95, 0.94, and 0.84, respectively, and are well balanced. With perfect recall (1.00), all the Sandy samples were correctly identified. The clayey soil also showed good performance in terms of F1 Score (0.82). Using the macro and weighted averages for precision, recall and F1-score, the model maintains a balance in performing well on all classes with scores around 0.91–0.92. All the results indicate that CNN model is very efficient in soil classification and has a little limitation in the classification of Red soil and good predictive reliability in most of the soil classes.

4.1.4 Confusion Matrix

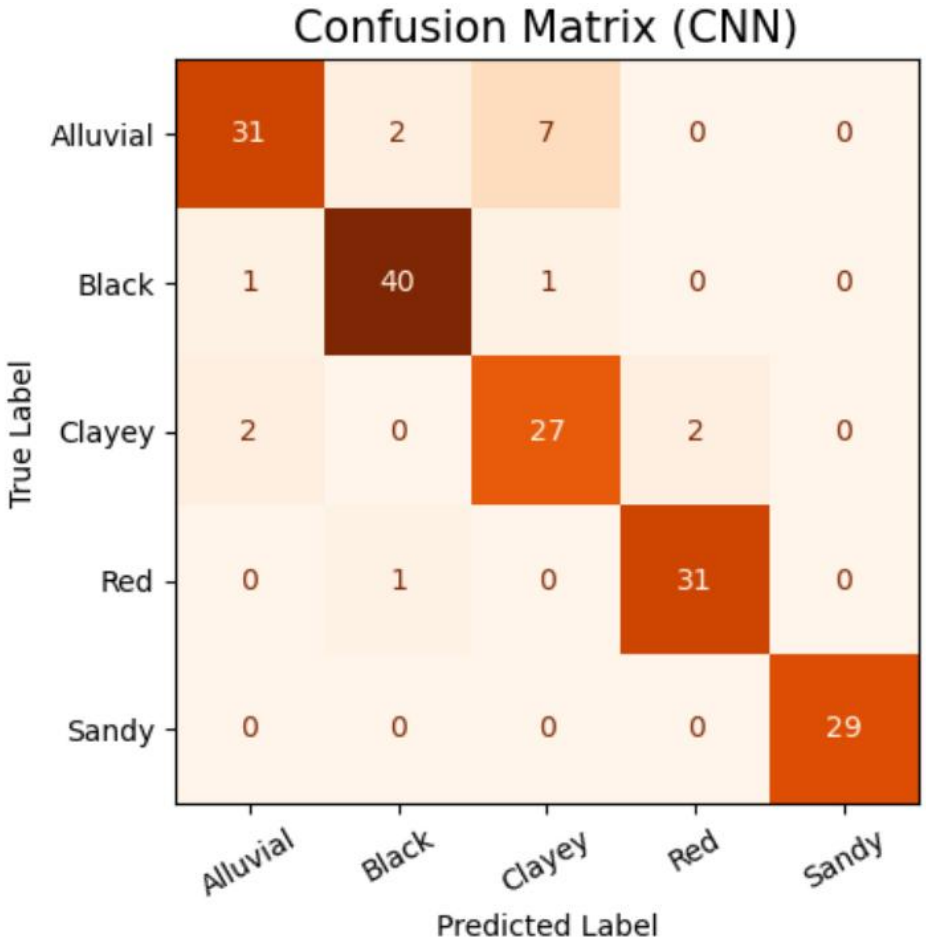


Fig. 11 Confusion Matrix of CNN

The confusion matrix of CNN indicates the accuracy of the model for the five soil types: Alluvial, Black, Clayey, Red and Sandy. The majority of the values are on the diagonal which indicates that the model was predicting the majority of soil samples appropriately. The model attained an accuracy of 100% in Red soil as it correctly classified all the 31 samples. The other soil type, with sandy soil, also performed well, with all 29 samples correctly predicted. The model was able to appropriately classify 40 samples of Black soil and only misclassified 2 samples as Alluvial and Clayey soil. For Clayey soil, the model also had a good performance with 27 out of 31 samples correctly classified. Only a few samples were misclassified as Alluvial or Sandy soil. The accuracy of the Alluvial was still lower than the rest of the categories, though. In all samples, 31 samples got correct classification while some samples had been misclassified as Black and Clayey. This can occur due to similarities of characteristics of Alluvial soil to other soil types as shown in Fig. 11.

4.1.5 Missing Classification

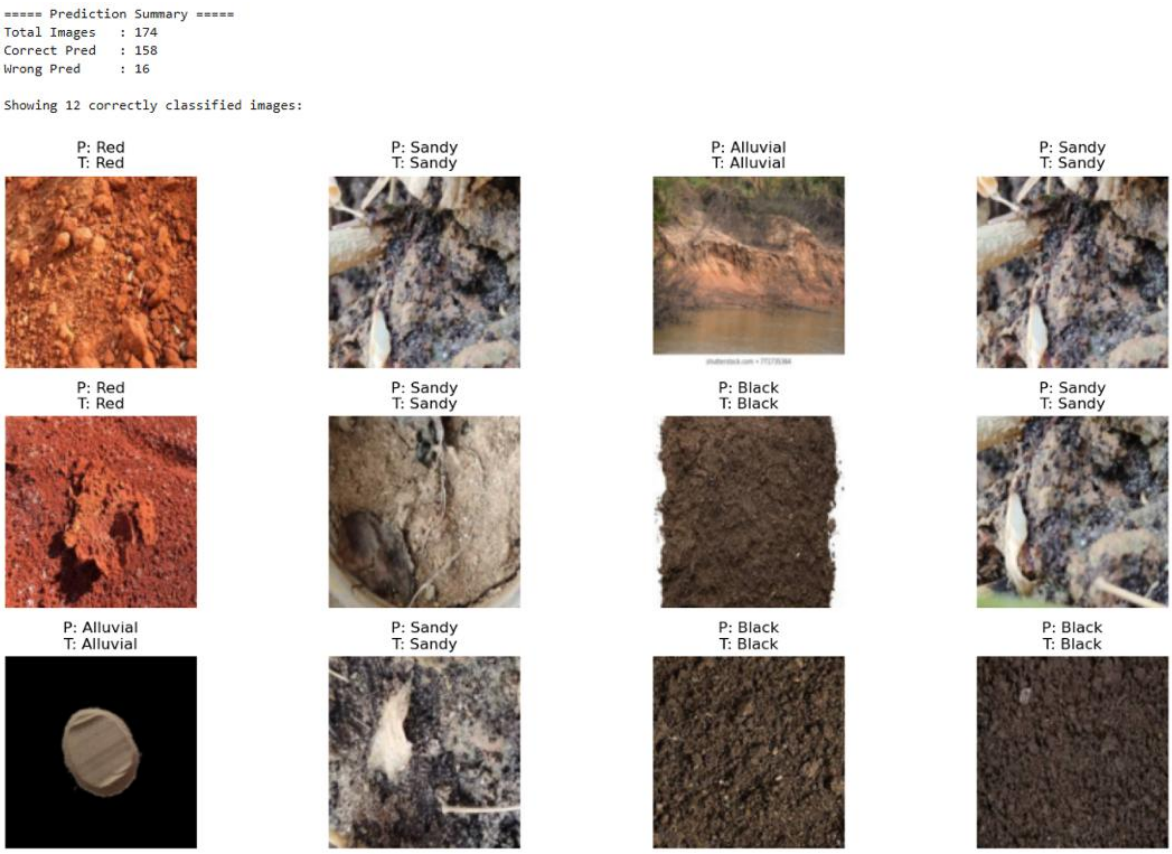


Fig.12 Correctly classified images of CNN model

The Fig. 12 shows the prediction summary of a model to classify the soil examined with 174 test images. This model correctly predicted 158 images and incorrectly predicted 16 images, resulting in an overall accuracy of ~90.8%. The samples shown are 12 images that are correctly classified with the predicted label (P) being identical to the true label (T). The images are grouped into four types of soil: Red, Sandy, Alluvial, Black. The images are labeled with the predicted class and the actual class, displaying that the model is able to appropriately classify the different soil classes according to their visual features. The reddish images of red soil, the coarse appearance and light-colored texture of sandy soil, layered sediment of alluvial soil, and the dark fine-grained texture of black soil. This proposes that the model has been able to learn the characteristics of each soil class correctly, given the high rate of correct predictions. While 16 images were misclassified, the achieved performance demonstrates that the proposed classification method is well suited and reliable for automated soil type identification, thereby enabling applications like precision agriculture, soil maps and crop recommendation systems.

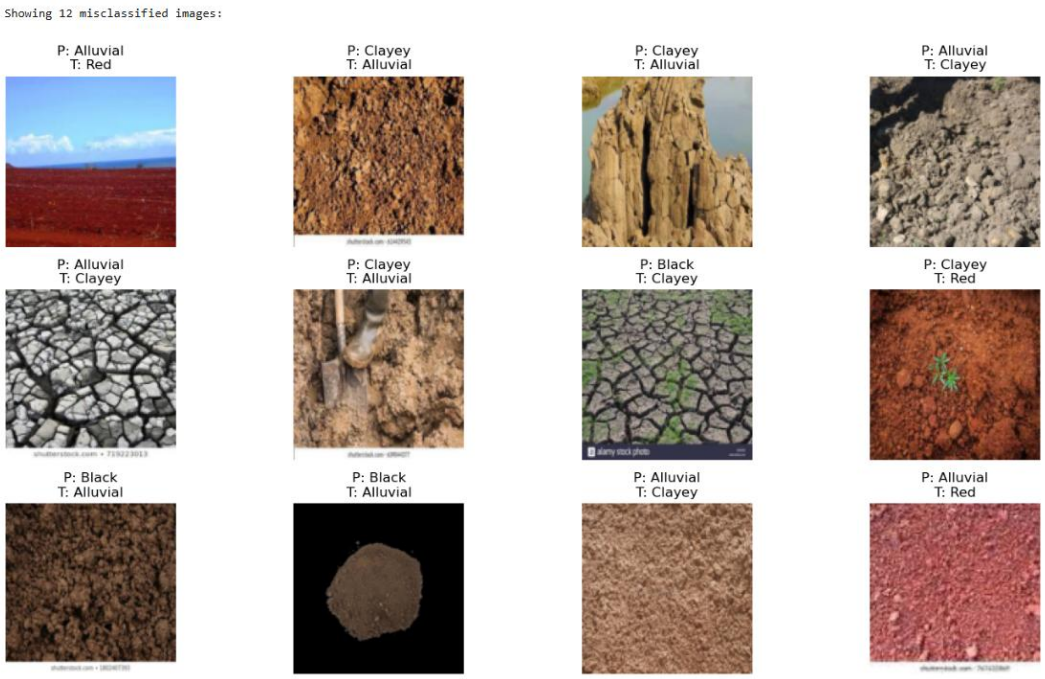


Fig.13 Misclassified Images of CNN model

The Fig.13 shows 12 misclassified soil images by the proposed soil classification model. The graph shows each sample's predicted label (P) and its true label (T), with samples that do not match color-coded. The graph is plotted to show each sample predicted label (P) and true label (T) with the samples that do not match in color coded. These misclassifications are mostly within the Alluvial, Clayey, Red and Black soil groups. For instance (in the Red soil images), some images are misclassified as Alluvial or Clayey, and in the Alluvial soil, some images are misclassified as Clayey or Black. Likewise, a few Clayey soil samples are labeled Alluvial or Black. The errors indicate that the model has a problem when the soil types have different visual characteristics, such as color, texture, moisture, or surface patterns, but they are all the same. The light intensity, image quality, and background elements may also cause inaccuracies in the prediction. Despite such misclassifications, the overall number of errors is relatively small (16/174 test images), which means that the model still has a good performance overall. The results from the analysis of these misclassified samples offer insights for future enhancements, such as expanding the dataset to comprise more diverse shapes, shapes with different texture or spectra characteristics, and/or using more sophisticated image pre-processing techniques to progress the model's classification accuracy and robustness.

4.2 Hybrid Convolutional Graph Neural Network

4.2.1 Train Accuracy Graph

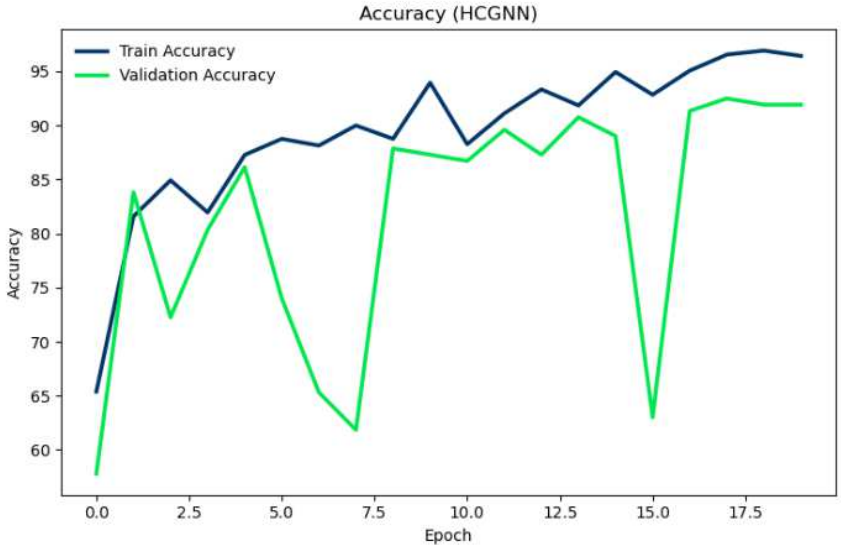


Fig.14 Train Accuracy and Validation Accuracy of HCGNN

The training and validation accuracy of HCGNN during the 20 epochs is plotted as in Fig. 14. It begins to train at about 65% accuracy and continues to improve, reaching about 97% accuracy at the end of the training. This means that the model is making good use of the training data. However, there are some fluctuations in the validation accuracy during the early epochs, reaching nearly 62% around epoch 7. Following that it gets much better and stays above 87% for most of the time. It is seen that the accuracy for the validation set drops to ~63% around epoch 15, and then rises rapidly to >90% in subsequent epochs. The validation accuracy leveling off at about 92% at the end epochs with training accuracy leveling off at about 97%. In general, the graph shows that HCGNN has successfully learned on the training set and has good generalization, though there is a minor fluctuation in the validation accuracy, which suggests that the learning process may occasionally get stuck.

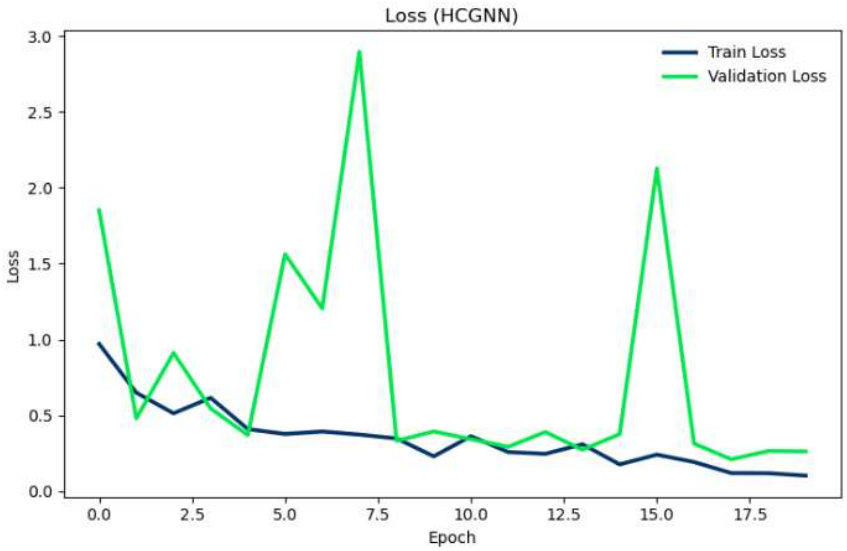


Fig.15 Train Loss and Validation Loss graph of HCGNN model

This Fig.15 shows the losses during training and validation of the HCGNN model over 20 epochs. The training loss is decreasing from its early value of ~0.98 to the final value of ~0.10, with the trend evident. This means that the model is continually learning and getting better at predicting the training data. The validation loss, on the other hand, varies significantly during training. It is initially reduced and then several very large peaks are seen, especially at epochs 5, 7 and 15. The biggest validation loss is at epoch 7, which is around 2.9. The fluctuations, however, are followed by a decrease in the validation loss that stabilizes at about 0.25 at the end of epochs. In general, the training loss markedly reduced, and the final validation loss is relatively low, demonstrating that the HCGNN model is able to learn effectively. The spikes in the validation loss during training are only temporary and result from some instability during training, but the model generalizes well.

4.2.2 Test Accuracy Graph

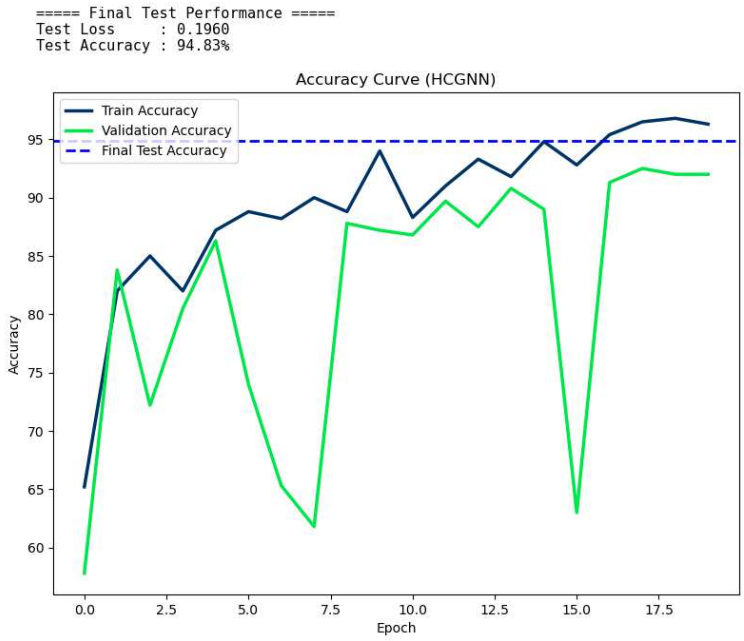


Fig. 16 Test Accuracy of HCGNN model

The Fig.16 shows the training, validation and final test accuracy of the HCGNN model for 20 epochs. The overall trend of the training accuracy is increasing, starting from around 65% and ending at almost 97% at the end of the training. The accuracy of the validation set is very unstable in the first few epochs, ranging from about 62% to 88%. It is typically above 85% accuracy throughout the epochs, dropping to around 63% at epoch 15. It recovers quickly and is approximately 92% in the last epochs. The dashed horizontal line shows the final test accuracy of 94.83%, demonstrating good performance on test data that was not used for training. The final test loss is relatively low (0.1960). In general, the HCGNN model shows good learning, high accuracy and good generalization ability, with a good final test accuracy, although the validation accuracy fluctuates a bit.

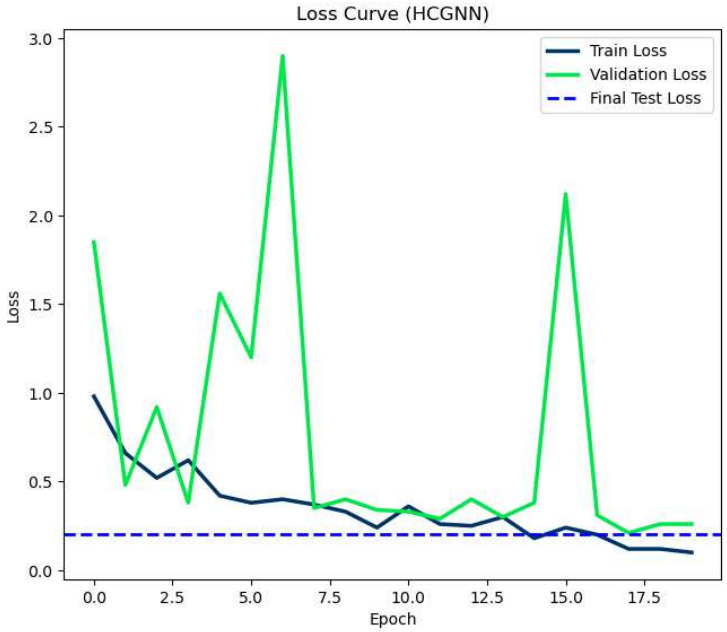


Fig. 17 Loss Curve of HCGNN

The loss of HCGNN model is plotted using the training loss and the validation loss for 20 epochs as shown in Fig. 17. The training loss generally decreases from around 0.98 in the first epoch to nearly 0.10 by the final epoch, indicating that the model gradually learns the training data effectively. The validation loss, on the other hand, has significant variations, peaking in epochs 5-7 and again at epoch 15. The validation loss drops to a relatively low level, however, after these peaks, and this loss level stays relatively low, primarily between 0.2 and 0.4. The dashed blue line represents the final test loss of about 0.20. Overall, there is a slight improvement in the training loss, which indicates a good learning performance, and the fluctuations of the validation loss suggest some instability during training. However, the relatively low final test loss indicates that HCGNN model has reasonable generalization ability for unseen data.

4.2.3 Classification Report

Table. 4 Classification Report of HCGNN model

Soil Type	Precision	Recall	F1-Score
Alluvial	0.90	0.90	0.90
Black	0.97	1.00	0.98
Clayey	0.90	0.85	0.88
Red	0.98	1.00	0.99
Sandy	1.00	1.00	1.00
Accuracy	—	—	**0.95**
Macro Average	**0.95**	**0.95**	**0.95**
Weighted Average	**0.95**	**0.95**	**0.95**

The classification report indicates that the HCGNN has high accuracy in the five soil classes: the test samples of 174 were classified and the overall success rate of the model was 95% as summarized in Table 2. The model achieves a macro-average and weighted-average precision of 0.95 and a recall of 0.98, with an F1-score of 0.95, showing good average accuracy and reliability in classification. However, for the classes, Sandy soil results in a perfect accuracy of 100% in terms of precision, recall and F1-score, indicating that all samples of Sandy soil are correctly recognized. The Red and Black soils also have a good performance with F1 scores of 0.99 and 0.98 respectively. Alluvial soil is consistently classified with 0.90 precision, recall and F1-score. The class with the lowest performance is Clayey soil with an F1-score of 0.88, primarily because of a slightly lower recall value (0.85), which means that some Clayey samples were incorrectly classified. In general, the results showed that the HCGNN model give accurate and balanced predictions for various soil categories, which proved that the model has a noble generalization capability and is appropriate for soil category classification.

4.2.4 Confusion Matrix of HCGNN

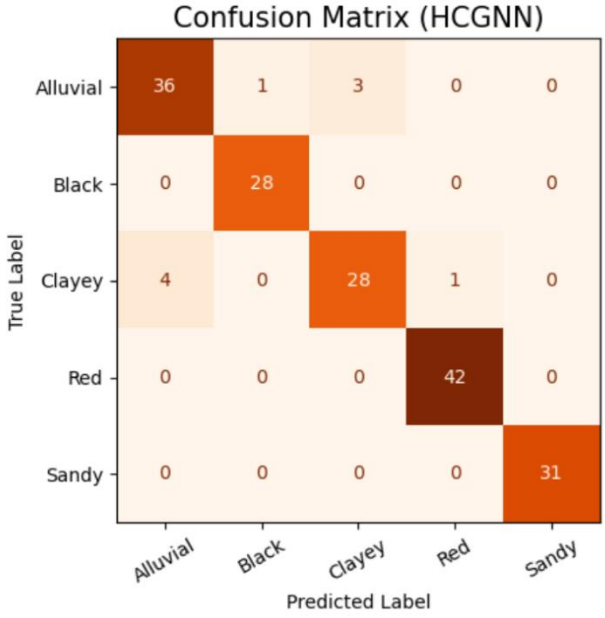


Fig. 18 Confusion Matrix of HCGNN

The confusion matrix is shown in Fig.18, indicating that the HCGNN model is able to classify the five soil types very well. The numbers on the diagonal of the matrix are relatively high, indicating that most of the samples are correctly classified. The model correctly identifies 36 Alluvial, 28 Black, 28 Clayey, 42 Red and 31 Sandy samples. There is no misclassified sample for any of the black, red or sandy soils. There are some faults in Alluvial and Clayey soils. In particular, 1 Alluvial sample is predicted to be Black and 3 Alluvial samples are predicted to be Clayey. Likewise, 4 Clayey sample are classified as Alluvial and 1 Clayey sample is classified as Red. These minor errors indicate that there are some similarities in the properties of Alluvial and Clayey soils, and

they may be somewhat more difficult to differentiate. In general, the HCGNN model is highly accurate and reliable, with a few classification errors and great performance for every soil categories.

4.2.5 Missing Classification

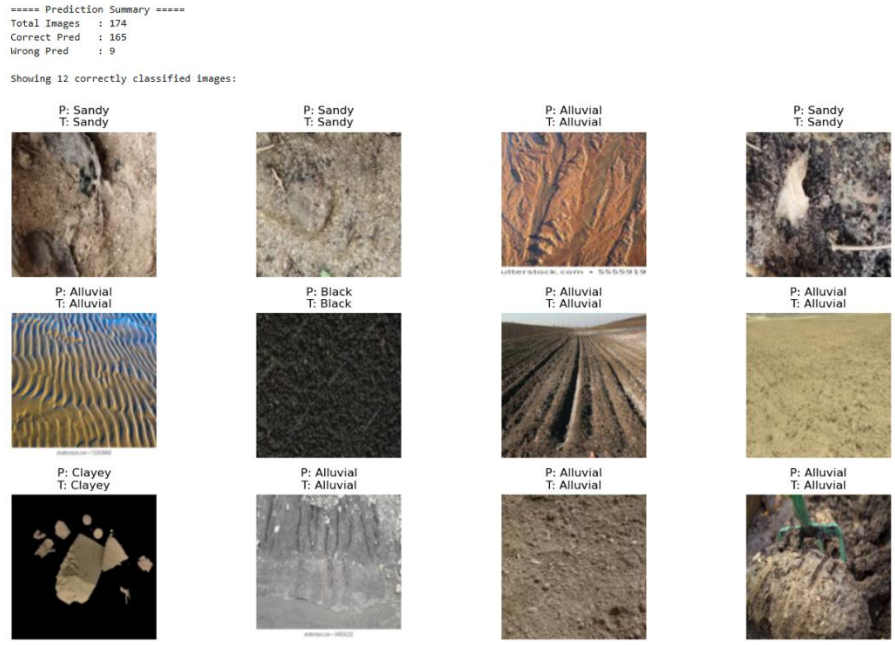


Fig. 19 Correctly classified Images of HCGNN model

The Fig. 19 is a summary of the performance of the soil classification model. It correctly classified 165 of 174 test images, and misclassified 9, giving the model an overall accuracy of about 94.8%. The images shown are examples of correct classification—when the predicted classification (P) is the same as the actual classification (T) for soil types like Sandy, Alluvial, Black, and Clayey. The percentage of correct predictions is high, indicating that the model is able to clearly discriminate between the various soil classes. The overall results show the good performance of classification and it is recommended that the model is usable for soil type identification.

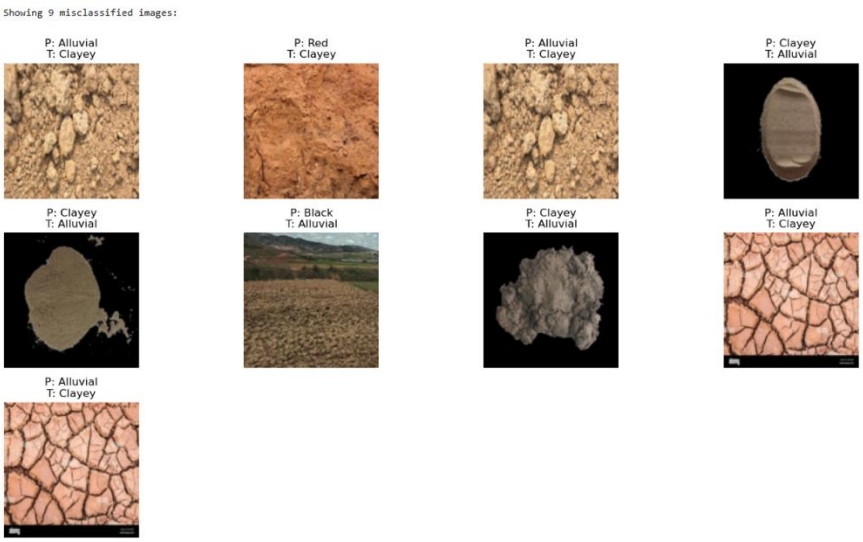


Fig.20 Misclassified Images of HCGNN model

The Fig. 20 shows the 9 misclassified soil images of the test set. In each image, the model prediction (P) is displayed with the actual soil label (T), and the difference between these two labels is shown, where predictions differ from the actual labels, which are soil types. The number of errors were mainly within Alluvial and Clayey soils and a few were with Black and Red soils. These misclassifications indicate that certain soil types have similar surface characteristics, color or texture making it hard for the model to make the distinction. The inclusive performance of the model is good with low number of misclassified samples, showing that the model has noble classification capability.

4.3 Comparison of CNN with HCGNN



Fig. 21 Confidence of CNN model



Fig. 22 Confidence of HCGNN model

This Fig.21 and Fig.22 shown the both CNN and HCGNN models correctly classify the input image as Alluvial soil, with the prediction results showing the same. Their confidence scores vary greatly, however. The HCNN model, on the other hand, only predicts the soil type with 87.41% confidence, while the HCGNN model has a higher accuracy of 97.50%. This improvement in more than 10 percentage points indicates the certainty and reliability of recognizing the soil class at which HCGNN works. The improved confidence of HCGNN shows that it better captures the information from local image features and the complex spatial relationships than the traditional CNN. Therefore, HCGNN is less prone to mis-classifying similar soil types, and makes more meaningful predictions. This increased confidence can enhance soil properties prediction in applications like precision agriculture, soil mapping, and land management. The model HCGNN was the preferred model for soil prediction due to its high confidence score (97.50%) and reliability. The outcomes indicate that HCGNN is superior to the traditional CNN model in term of prediction accuracy and confidence, thus it is more effective approach for automated soil classification.

4.4 Performance Comparison of HCGNN and CNN

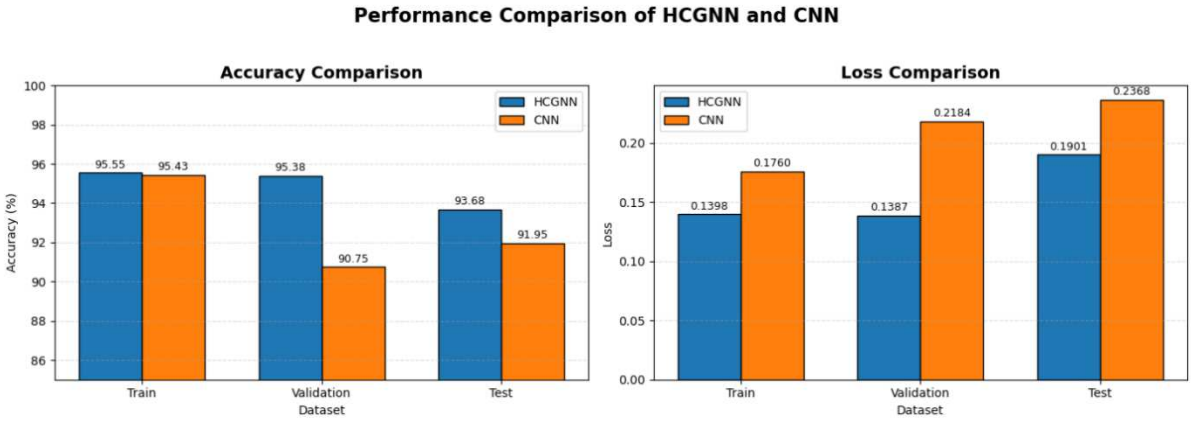


Fig. 23 Performance comparison of HCGNN and CNN model

The plot compares the performance of HCGNN and CNN models in terms of accuracy and loss on training, validation, and testing datasets. As for the accuracy of the models on the training set, HCGNN reaches a 95.55% accuracy while CNN reaches a 95.43% accuracy. During the validation step, however, there is a huge margin with HCGNN achieving 95.38% accuracy and CNN 90.75%. When tested on the test dataset, HCGNN is again better than CNN with accuracy of 93.68% and 91.95% respectively. The loss comparison also shows the superiority of the HCGNN model. HCGNN achieves smaller loss values on all datasets, with training, validation and test losses of 0.1398, 0.1387, and 0.1901, respectively. In contrast, CNN exhibits higher losses of 0.1760, 0.2184, and 0.2368. Lower losses mean it is better learned and more generalizable. As shown in the Fig. 23, HCGNN is capable of consistently outmatching the traditional CNN model in terms of accuracy

and loss. This implies that HCGNN performs better and more reliably with classification problems, and is more suitable for achieving better predictive performance.

4.5 Performance Evaluations

The HCGNN model was found to be more effective with the highest confidence score of 97.50%, after comparing the CNN and HCGNN model. The HCGNN model was chosen for greater crop prediction and analysis based on this performance. Crop prediction is carried out by feeding appropriate data as text input to the trained HCGNN. The model takes the input features and uses the patterns it has learned from the data to predict which crop is most appropriate. Several visual analyses are also provided to help to understand the data and to support the results of the predictions. A feature distribution graphically shows the variation and the spread of important features that are used to input the data. The crop distribution is a component of the crop distribution that reflects the number of samples available in each crop category, and is used to evaluate the balance of the sample. The feature correlation heatmap shows the relation between the different features and helps to identify which features are strongly or weakly correlated. Also included is the crop vs soil type analysis, which shows the relationship between various soil types and crops grown.

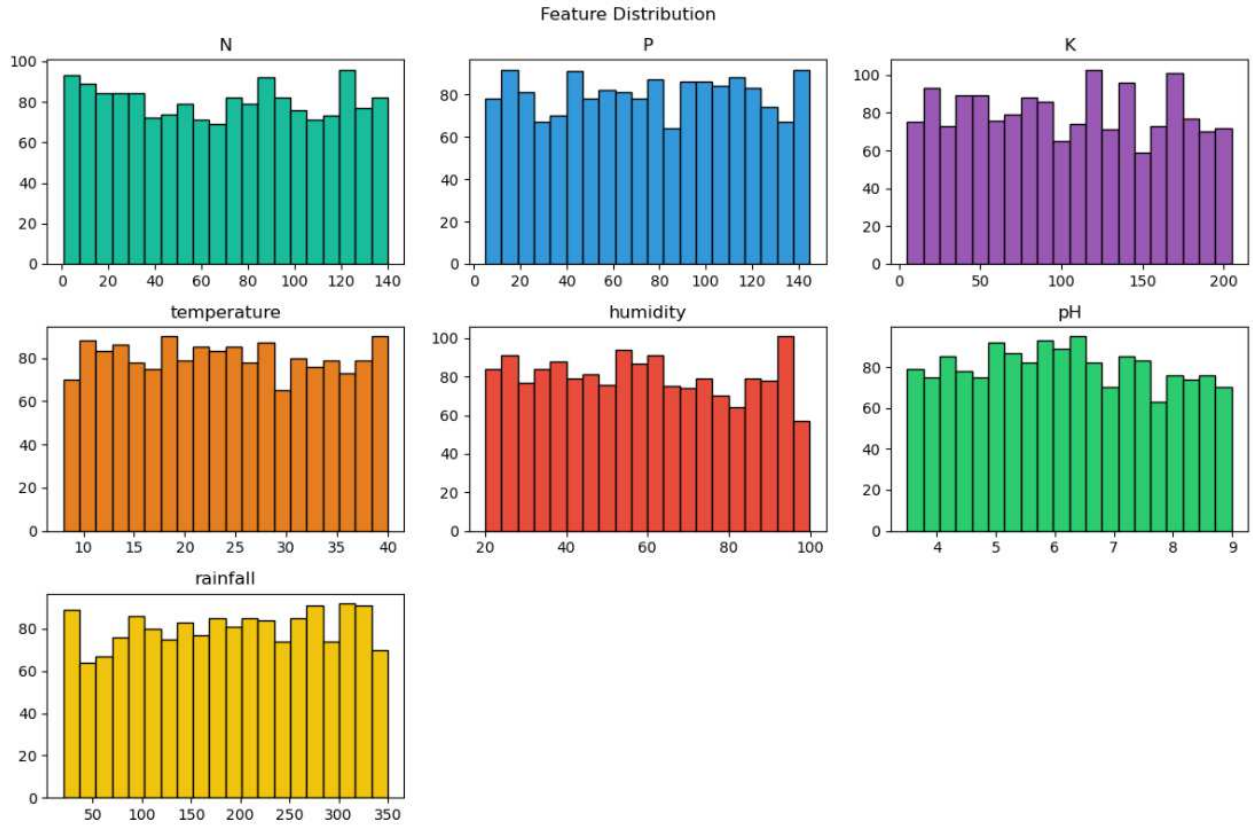


Fig. 24 Feature Distribution of Text dataset

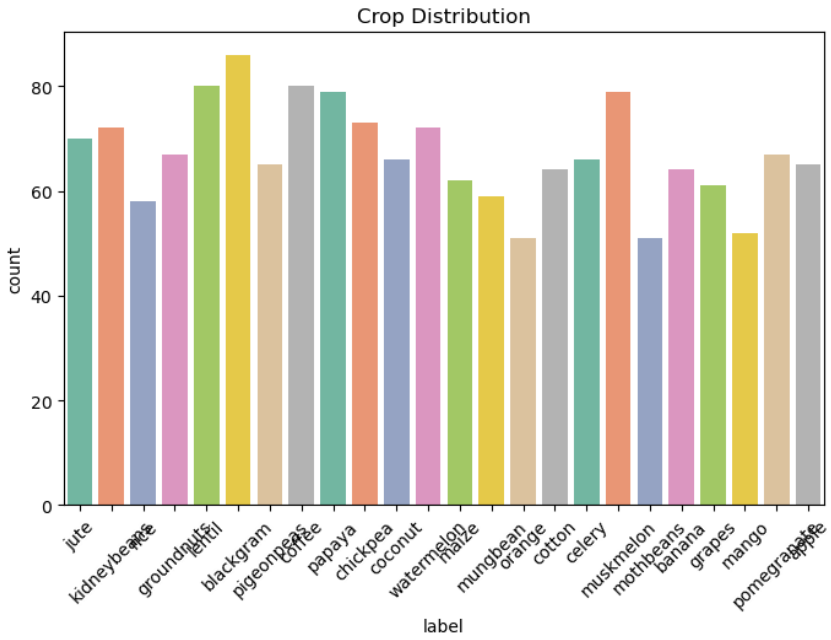


Fig.25 Crop Distribution

The fig-26 shows the distribution of the different categories of crops, according to the number of samples. The number of samples range depending on the crop; most have 50 to 85 samples. Black gram has the maximum number of samples around 86 followed by groundnut and pigeon pea with around 80 samples. Mung bean and muskmelon, on the other hand, have relatively low counts, of around 51 samples each. Moderate representation is observed for most other crops such as rice, papaya, coconut, cotton and mango. In conclusion, the graph shows that there is some variability in the number of samples for each crop category, which can affect the accuracy of a machine learning model trained on this data.

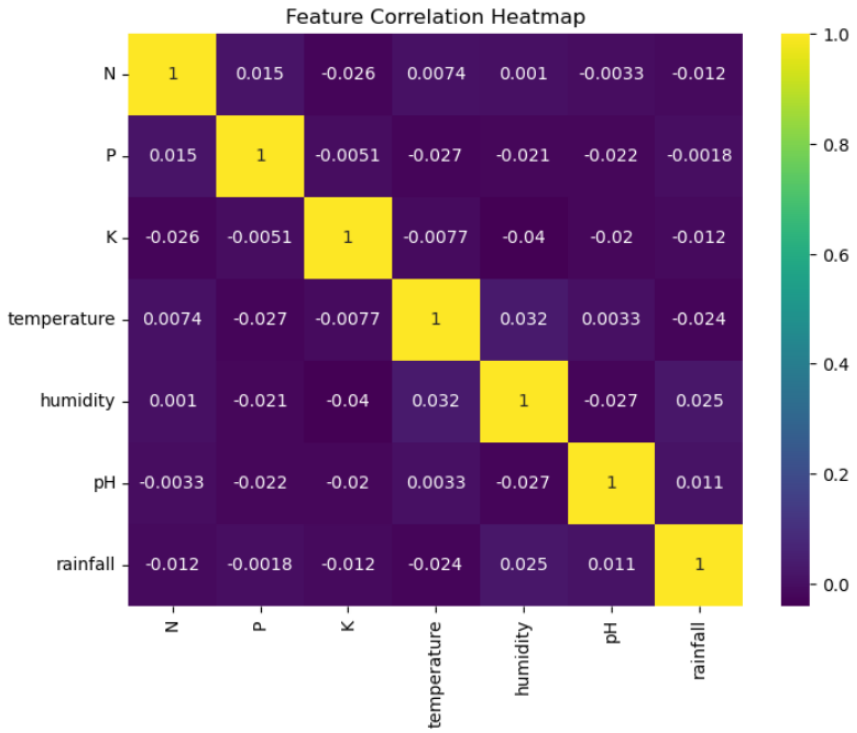


Fig. 26 Feature Correlation Heatmap

The Fig.26 shows the correlations between the variables: N, P, K, temperature, humidity, pH, and rainfall. The correlation values are very close to zero suggesting that there is almost no linear correlation between these variables. The strongest negative correlation is between potassium and humidity (-0.04), and the strongest positive correlation is between temperature and humidity (0.032). Overall, the graph indicates that these features are mostly independent of each other. This information can help in understanding the relationships among soil nutrients and environmental conditions.

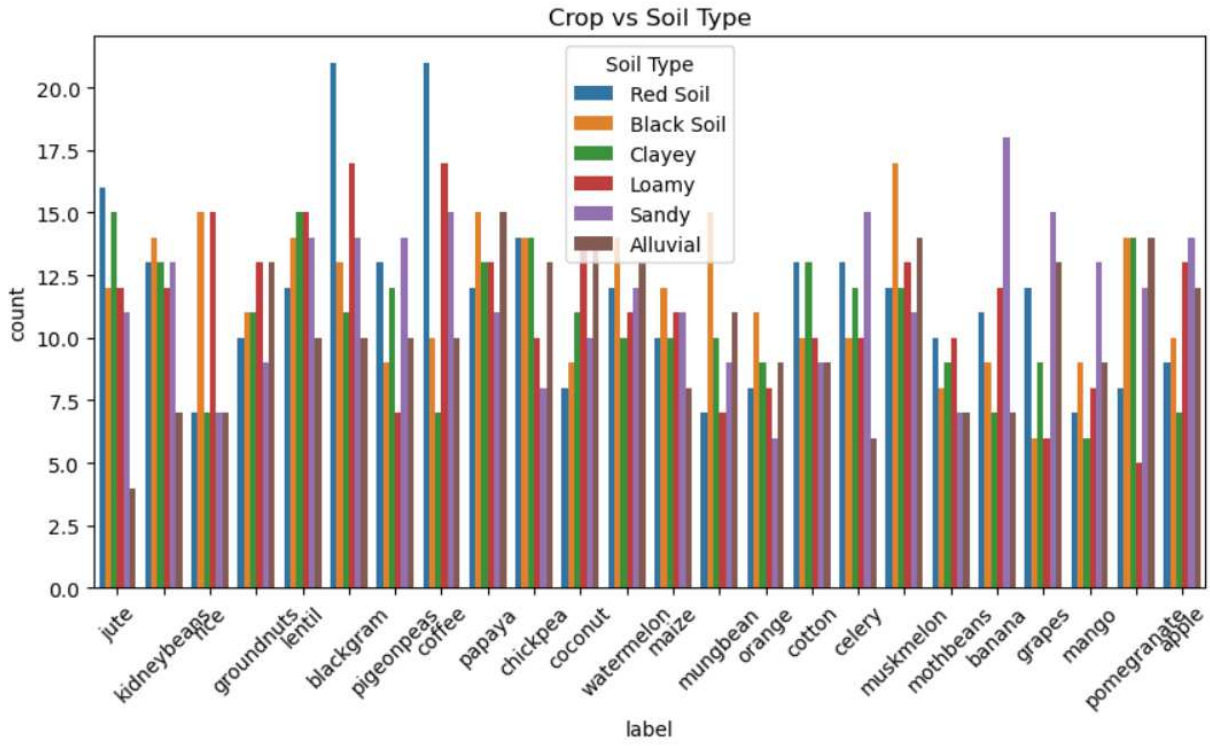


Fig. 27 Comparison of Soil type with Crop

The relationship between different crops and soils such as red, black, clayey, loamy, sandy, and alluvial soils is shown in the fig. 27. It indicates the soil type dependence of crop distribution. The higher number is noticed for crops like black gram, pigeon pea etc in red soil and for banana in sandy soil. There are also significant numbers of black soil plants such as mango and celery. Other crops (jute, cotton, papaya and grapes) have different distributions based on soil types. Overall, the graph shows the variety of cropping on the different soils.

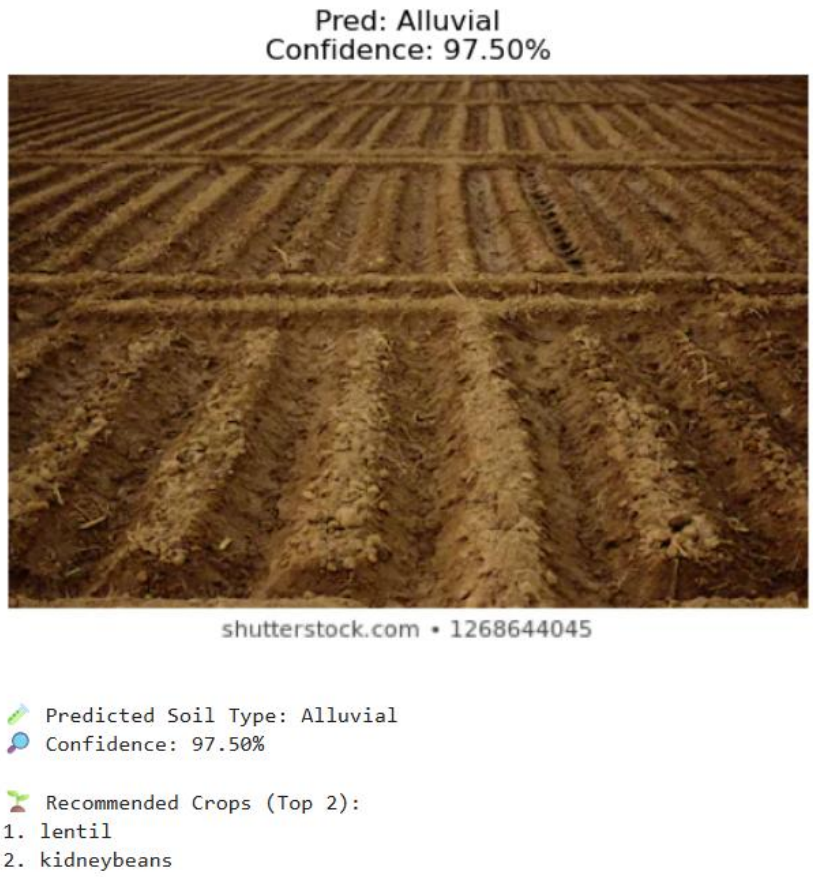


Fig. 28 Prediction of soil and crop in HCGNN model

This Fig.28 shows the output of the soil classification model for a test image. The model predicts the input as “Alluvial soil” with a prediction confidence of 97.50% which is a high level of confidence in the prediction. This is a field of cultivated agriculture that seems to be well-managed and has the texture and characteristics of an alluvial soil. The system also suggests two most appropriate crops as lentil and kidney bean depending on the predicted soil type. These recommendations are part of a crop recommendation module which associates soil type with appropriate crop variety. The high confidence score specifies that the model can effectively recognize soil properties from images, making it a reliable tool for soil identification. The system can be used by the farmers to help them choose crops appropriate to the soil type determined by soil typing. This can be used to improve the productivity of the agricultural operations, optimize the use of land, and support decision-making in precision farming.

5. Discussion

The results of this research prove that the projected HCGNN outperforms CNN model in predicting crop. A comparison of the two models illustrates that HCGNN outperformed in terms of accuracy for both training, validation and testing data sets and also provided lower loss values. This indicates

that HCGNN is able to learn important patterns from the input data more effectively and generalize better to unseen data. Further, its testing accuracy of 93.68% further validates its reliable predictive capability. One significant result about HCGNN is that the highest confidence level obtained for the prediction of the crops was 97.50%. This level of confidence gives us the idea that the model will make accurate predictions if appropriate features are provided. The combination of CNN and GNN ideas enables the model to learn feature-level information and the relationships among the input data, which can help enhance its performance. The feature distribution and crop distribution plots give a clearer idea of the data set, and the differences between each crop category. The correlation heatmap allows for identification of relationships among the important features and the crop-versus-soil-type analysis gives information on the association among soil characteristics and crop selection. These visualizations can help to interpret the prediction process and make the predictions generated by the model more supportive.

Table. 5 Performance Comparison of CNN and HCGNN

Model	Training Accuracy (%)	Validation Accuracy (%)	Testing Accuracy (%)	Highest Confidence (%)
CNN	95.43	90.75	91.95	**87.41**
HCGNN	**95.55**	**95.38**	**93.68**	**97.50**

The performance comparison among CNN model and HCGNN model is shown in Table. 5. The accuracy of HCGNN in both the training and the validation sets was higher than CNN, with a training accuracy of 95.55% and a validation accuracy of 95.38%, respectively, and a testing accuracy of 93.68%. Moreover, the HCGNN model achieved the highest confidence value during the crop prediction, i.e., 97.50%. From these results, it can be seen that HCGNN has better prediction performance and is more reliable and stable than the traditional CNN model.

6.Conclusion & Future Work

This paper used two models for image classification and prediction of crop. First, soil images were collected from Kaggle website and preprocessed. Then, two models were applied: a Hybrid CNN and a Hybrid GNN. Compared to the Hybrid CNN, the Hybrid GNN performed better, achieving 97.50% accuracy. Because the hybrid GNN model achieved better accuracy, we used it to predict the crops. The proposed Hybrid GNN model has successfully classified soil images with an accuracy of 97.50% and can be used for crop prediction, but there is scope for further improvement.

Further research could include taking images from other regions, soil types and weather conditions to increase the amount of soil and crop data in the model and thereby increase its reliability.

The model can also be incorporated into a smart phone or web application to offer farmers real-time crop recommendations with their images taken on the smart phone. Moreover, the inclusion of some relevant parameters like soil pH, soil nutrients, soil moisture, soil temperature, and weather condition may enhance the accuracy of the prediction. The improvements might help the model be more applicable, efficient and beneficial for sustainable agriculture.

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Author contributions

All authors contributed to the study conception and design, Material preparation, data collection, and experimental setup were performed by Ramesh Patra, Mamata Garanayak, and Bijay Kumar Paikaray. Data analysis and statistical evaluation were carried out by Chinmaya Kumar Naik and Trilochan Rout. The first draft of the manuscript was written by Ramesh Patra, and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Data availability

https://www.kaggle.com/datasets/jayaprakashpondy/soil-image-dataset

https://www.kaggle.com/datasets/shuvokumarbasak2030/soil-environment-analysis-dataset

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