2022 IEEE 4th International Conference on Cybernetics, Cognition and Machine Learning Applications (ICCCMLA) | 978-1-6654-6246-4/22/$31.00 ©2022 IEEE | DOI: 10.1109/ICCCMLA56841.2022.9989293

A study on Deep Learning based Soil Classification

Prabhavathi V
School of Computer Science and Engineering
VIT-AP University
Vijayawada, India
0000-0003-0521-6022

Kuppusamy P
School of Computer Science and Engineering
VIT-AP University
Vijayawada, India
0000-0001-5369-8121

***Abstract*—Soil selection for good crop yielding plays a vital role and is a challenging task for farmers. Classification of soil requires analyses of features and characteristics of various soil of different regions. Soil can be classified based on its features like texture, particle size, and color by applying computer vision and image processing. However, deep learning-based soil classifications are producing better results. In Computer-based Soil classification, various Machine Learning algorithms such as K Nearest Neighbor, Quadratic Regression, Support Vector Machine (SVM), Naive Bayes, Decision Tree, Random Forest, Multi-Layer Perceptron (MLP), and Neural Networks are applied for soil classification by various researchers. The end-to-end process facilitated by deep learning largely reduces addiction to preprocessing techniques and spatial form designs. This paper is mainly focused on the study of various deep learning algorithms that are applied for soil classification. It talks about the varieties of features and databases used by researchers for soil classification using various deep learning techniques. Evaluation metrics are analyzed and shown for discrimination. Finally, a novel deep learning model for better soil classification is also proposed as our contribution to this study. This study helps the researchers understand various deep learning approaches implemented for soil classification. It also acts as a model to implement improved deep learning techniques in future research works.**

Keywords— Machine Learning, Deep Learning, Convolutional Neural Network, Agriculture, Soil classification

I. Introduction

The world population is increasing day by day, which needs an increase in the production of food, fabrics, and medicines parallellyon the same scale for their survival on this globe. Agriculture is the main source that can serve the rising demands in this regard. Soil is an essential tool for agriculture that contains nutrients required to grow crops. Various varieties of soil are available in a particular country and numerous varieties are observed all over the world. There is a need for precise classification of soil such that formers can choose which crop to grow based on the soil nutrition, and physical and environmental conditions to achieve a good yield. In this regard to help the formers deep learning techniques are being applied for analyzing the soil and recommending suitable crops. The deep learning technology is based on neural networks with representation learning. It is used for data analysis and image processing applications producing encouraging performances. In various domains like visual recognition, entertainment, healthcare, fraud detection, game playing, language translations, etc., deep learning has been implemented successfully. Recently Deep learning is being applied for different agriculture applications and obtaining the best performances.

A. Deep Learning Algorithm

The deep learning concept was proposed by Hinton in 2006. It is a technique with which a computer system can improve with experience and data. Deep learning is a type of machine learning. The flexibility and power of deep learning are achieved with the representation world in terms of a nested hierarchy of concepts. Each concept is defined in terms of simpler concepts and hence more complex representations can be computed with the help of less abstract ones. Deep learning utilizes an architecture with a greater number of layers through which it can perform the conversion of raw data into features called feature engineering. The feature extraction or selection can be done automatically and the desired output can be obtained. The structure of a deep network consists of a large number of neurons where they are connected to many other neurons. The function of the network will be determined with the help of weight (connection strength) between the neurons during its learning process. The main varieties of deep learning algorithms include Convolutional Neural Networks, Deep Belief Networks (DBNs), Long Short-Term Memory (LSTM), Multilayer Perceptron, and Autoencoders.

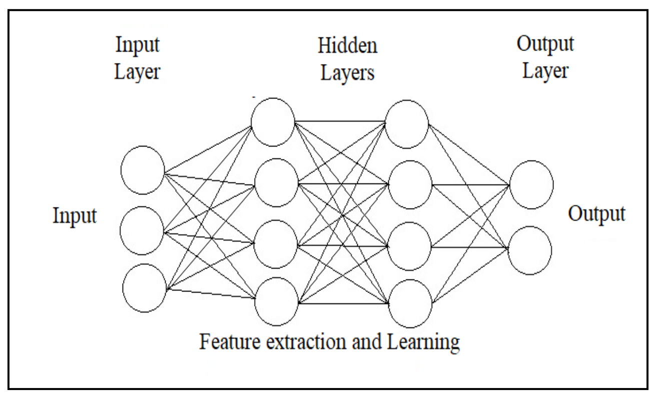

Fig. 1. A typical deep learning model

B. Convolutional Neural Network (CNN)

The first Convolutional Neural Network called LeNet was developed by Yann LeCun in 1988 and used for character recognition. A CNN is usually applied for the analysisof visual images by processing data with the help of a grid-like topology. CNN is a feed-forward neural network and is widely used for the classification of objects in an image. CNN is used in agriculture applications like land cover classification, weed detection, disease detection, crop yield prediction, fruit counting, etc. In general, CNN is used for classification applications with a large amount of data. CNN has multiple hidden layers through which it can extract information from the image.

CNN structure consists of 4 different types of layers. They are the Convolution layer, Rectified Linear Unit (ReLU) layer, the Pooling layer, and the fully connected layer. The convolution layer consists of many filters to perform the convolution process. The convolution layer takes the input image and extracts important features after performing the filter operations. The feature map obtained by the convolution layer will be applied to the ReLU layer. ReLU performs non-linear functionality and prepares rectified feature map. This will be given to the Pooling layer and is used for dimensionality reduction purposes and the reconstruction process. It takes the input as rectified feature map and after the reduction process, it gives pooled feature maps. The flattening process will be applied to convert the two-dimensional pooled feature maps into a single continuous vector. This flattened feature map will be given to the fully connected layer to produce the final output. The convolutional layer functionality can be denoted mathematically as:

$$x^1 = g(w^1 * x^0 + b^1) \quad (1)$$

where the two-dimensional input image is represented by x^0, convolutional layer filters and bias are indicated by b^1 and w^1 respectively. x^1 represents the output feature maps and the convolution operation is denoted by $*$. ReLu activation function is denoted by 'g'. The artistry of CNN is that the number of parameters is independent of the size of the original image.

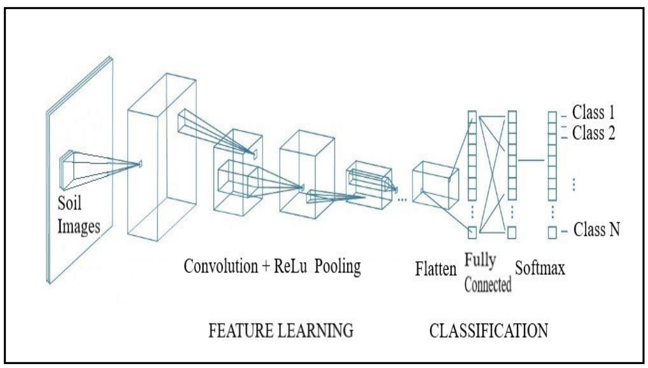

Fig. 2. CNN Architecture for Soil Classification

II. LITERATURE REVIEW

Deep learning techniques are employed in various agricultural and food production challenges. This section describes the deep learning techniques implemented by various researchers over the last five years given soil classification and predictions using various varieties of data. IoT-based agriculture system was developed to monitor soil parameters collected by using LM35, DHT11, DS18B20, and, soil moisture sensors through a Wireless Sensor Network (WSN) with many clusters of nodes. Using the LSTM network as the suitable algorithm, soil parameters are studied and the suitable crop was predicted. Another IoT system used additional parameters like soil type, land type, and the area sown along with the soil moisture level, humidity, temperature, and pH collected from the LM35 temperature sensor, DHT22 humidity sensor, and PH meter, and the crop prediction for cultivation was done using Deep Neural Network (DNN) [1],[5]. The problems of land cover classification, crop recommendation, land management, fertility recommendation, and smart agriculture have been approximated using deep learning. All the works employed notable CNN architecture and also used a deep learning framework [2].

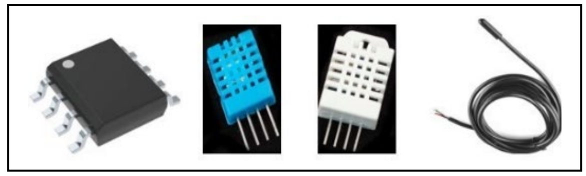

Fig. 3. LM35, DHT11, DHT22, DS18B20 Sensors. (Pictures taken from the Internet)

Soil quality can be maintained with the help of sustainable land management. For automatic soil fertility prediction of soil organic carbon, manganese, zinc, iron, and phosphorus pentoxide, a system was developed using a collection of networks, along with deep learning [3]. The deep CNN model is used for soil detection with hyperspectral bandscollected by satellite [4]. In Precision Agriculture (PA), a deeplearning-based automatic parcel extraction model was developed for the plain areas [6]. With its strong characteristic of feature extraction, Deep CNNs were implemented for the classification of hyperspectral images. Ensemble methods of CNN were usedand found that they provide remarkable potential in classifying images [7]. As per soil engineering soil is composite and ambiguous. Soil classification was made practically simple using an artificial Intelligent method with deep learning that can classify gravel, clay, and sand effectively [8]. In a systematic literature review incrop yield prediction where the soil is one of the important factors affecting crop yield, it is found that the most applied deep learning algorithm was CNN, and the other widely used were LSTM and DNN algorithms [9]. In a review on recommendation systems in agriculture, it is found that Neural Networks were used to find the solution for cold-start. By considering various soil properties a recommendation method was developed to recommend specific crops suitable for that particular land. In addition to that, the suitable land recommendation method was also advanced to find suitable lands for a specific crop based on its requirements [10]. Village-wise soil classification and predictions help in minimizing fertilizer expenditure, improve the health of the soil, and increase profitability. By using a fast-learning technique called Extreme Learning Machine (ELM) classifier with different activation functions, a Neural Network model was developed to solve soil nutrition deficiency problems [11]. Soil aggregates were classified using A deep CNN with disparate architectures. The overall accuracy of deep networks indicates their excellent performance in the classification of aggregates with stereo-pair images [12]. A deep convolutional generative adversarial network with Compressed Sensing was used for the prediction of soil PH values [13]. Using an SVM classifier a low-cost soil classification system was developed by analyzing the texture of soil images taken from a smartphone. Using a calibrated CNN model, a smartphone application was developed for the prediction of soil texture values for the soil images[14] [15]. A CNN classification model is used to classify the soil of six different land covers.

Multi-object detection in macro-images is enhanced using a CNN model [17],[25]. A review of deep learning approaches for soil classification shows that no requirement for preprocessing and spatial-form designs for the classification as the CNN can learn the features automatically [18].

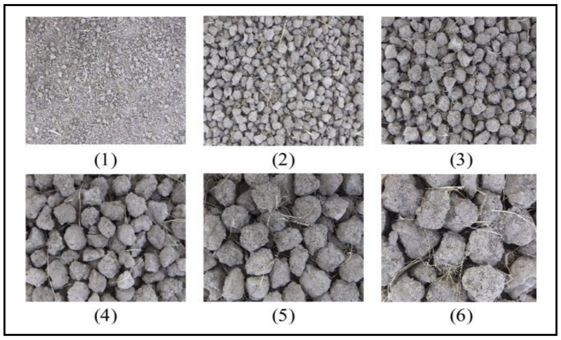

Fig. 4. Different types of Soil aggregates [12]

A recent comprehensive updated review on Machine Learning in Agriculture in the crop, water, soil, and livestock management, it is found that 10% of the studies were intended for soil management. And also, most of the models used in soil management were based on Neural Networks including deep learning [19]. Farmers need to choose precise crops based on location, season, and properties of the soil to avoid crop loss. Researchers recently proposed an Intelligent Crop Recommendation System that takes into consideration of environmental parameters, soil nutrient contents, and soil characteristics for the classification of the soil [20]. Deep learning is used to develop an energy-efficient optimal timetable rescheduling model for an Intelligent metro transportation system [16]. Nowadays categorization of images is carried out attractively using deep learning approaches. A Complex Valued CNN (CV-CNN) was developed for soil moisture estimation using Synthetic Aperture Radar data [21].

Fig. 5. Different types of soil samples [14].

An appropriate and efficient soil classification system based on deep learning was proposed to help the farmers to choose the correct soil type for their crop that can maximize the yielding of the crop [22]. A CNN-based soil classification, based on electromagnetic properties of the soil, was developed that uses Ground Penetrating Radar scanned images [23]. Another Deep CNN-based soil classification method was developed based on the chemical and physical properties of the soil [24].

III. Performance Metrics for Soil Classification

Performance metrics used for soil classification are briefly described in this section. As the performance of the algorithm depends on the metrics and it influences the significance of characteristics that are weighted, choosing suitable metrics is momentous. For classification problems, performance metrics compare the expected class label to the predicted class label or interpret the predicted probabilities for the class labels. Metrics are enforced during training as well as testing phases while performing classifications. Different types of classification metrics for classification problems can be listed as follows:

1. Confusion matrix
2. Precision
3. Recall
4. Accuracy
5. F1 Score
6. Area Under Curve (AUC)

A confusion matrix is a table representing four different combinations of predicted and actual values as shown in Table 1. The outputs can be visualized with the help of a confusion matrix and it is used to calculate the values of Precision, Recall, Accuracy, F1 Score, and Area Under the Curve.

TABLE I. Confusion Matrix

Predicted values	**Actual Values** *Positive*	*Negative*
Positive	TP	FP
Negative	FN	TN

True Positives (TP) indicate the number of times the model predicted YES and the actual output was also YES.

True Negatives (TN) indicate the number of times the model predicted NO and the actual output was also NO.

False Positives (FP) indicate the number of times the model predicted YES and the actual output was NO. This is also known as a Type 1 Error.

False Negatives (FN) represent the number of times the model predicted NO and the actual output was YES. This is also known as a Type 2 Error.

Precision can be described as the fraction of relevant instances among the retrieved instances. The formula can be defined as follows:

$$\text{Precision} = \frac{\text{Number of True Positives}}{\text{Number of Predicted Positives}}$$

The recall is also known as sensitivity. It represents the proportion of actual positives that are classified correctly. The formula is as follows:

$$\text{Recall} = \frac{\text{Number of True Positives}}{\text{Number of actual total Positives}}$$

Accuracy represents how many inputs are classified correctly. The formula is as follows:

$$\text{Accuracy} = \frac{\text{Number of True Positives } + \text{True Negatives}}{\text{Total observations}}$$

F1-Score is a function of Precision and Recall. It is used to find the balance between these two metrics. It determines how many instances the model classifies correctly without missing a significant number of instances. The equation of F1-Score can be represented by the following equation:

$$\text{F1-Score} = 2 \times \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

AUC / ROC (Receiver Operating Characteristics) Curve is a graph that shows the performance of a classification model at all thresholds. ROC is a probability curve and AUC represents the degree of separability. A higher valueof AUC shows better performance of the model.

IV. Observations From This Study

In this section we have described the process of our study, observations from the study, and our contribution to this study. In our study process, we have considered the past five years of publications related to soil classification using deep learning techniques including a few review papers. We have formulated two tables collecting the details regarding the deep learning techniques, soil features, and datasets used by the researchers for soil classification, along with the performance and scope of future implementations by carefully observing the selected publications. Tables II and III show the details of almostall reference papers excluding the review papers. Based on these details we have observed that the researchers used different varieties of features as input as well as different deep learning techniques are followed in the process of soil classification with different datasets in their research as described below.

TABLE II. Varieties of Soil Features and Datasets Used

Ref.	Soil Features	Dataset Used	Functionality
[1], [5]	Environment parameters	Data was collected using sensors as well as manually.	Soil analysis and crop prediction
[3]	Soil nutrients.	Data from Govt. of Maharashtra (India).	Soil fertility prediction
[4]	Satellite Images	WorldView-2 satellite data.	Soil detection
[6]	Soil nutrients.	Remote sensing images	Soil mapping.
[7], [17]	Soil images.	Hyper Spectral, near-infrared spectroscopy	Soil classification
[8]	Soil images	Smartphone soil images.	Soil Classification
[11]	Soil nutrients and PH	Marathwada dataset	Soil parameter classifications
[12]	Soil images	Aggregate stereo images	Soil Aggregate Classification
[13]	Soil pH value	P440 sensor data	Soil PH prediction
[14], [15]	Texture features	Smartphone soil images.	Soil Texture Classification
[21]	Soil images	Radar data	Moisture estimation
[23]	Electromagnetic properties	Ground Penetrating Radar (GPR) data	Soil classification
[24]	Satellite images	Landsat 8 Satellite data	Soil classification

A. Varieties of Features for Soil Classification

Researchers used several varieties of features for soil classification, in their research as shown in Table II. The selection of features is based on the availability of the dataset and the purpose of their research. Many researchers used nutrient features related to the soil to find out its propriety for a particular type of crop. These features can be categorized into three varieties as follows.

1. Soil nutrient parameters
2. Environment / Weather parameters
3. Physical / Visual parameters

Mainly focused soil nutrient properties are Soil Organic Carbon (SOC), availability of Nitrogen, Phosphorous, Potassium, Sulphur, Zinc, Boron, Iron, Manganese, Copper, Soil reaction (PH), and Electric Conductivity (EC). Environmental parameters like soil moisture level, soil humidity level, soil temperature, air temperature, and seasonal weather conditions are also considered. Most of the above parameters can be obtained either through testing of the soil by using traditional methods in the laboratory or through an IoT system using different types of sensors to collect different parameters as shown in Fig. 6.

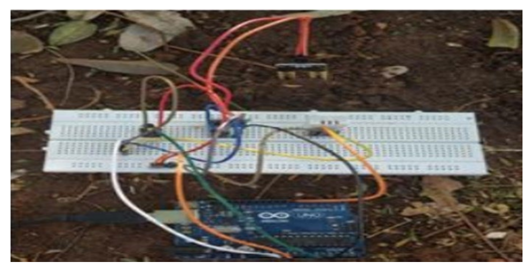

Fig. 6. IOT System for Soil data collection [5].

Physical or Visual parameters of the soil include soil texture, soil type, soil color, soil granules size, soil tillage aggregates, soil depth,soil drainage and erosion hazard, area of land to be sown, locality, etc. Most of these parameters will be extracted through deep learning by inputting soil images. Some parameters like locality, area to be sown, etc. can be collected manually. All the parameters will affect the agriculture process starting from the selection of the crop to be cultivated, seeds sowing time, germination process and time, growth of the crop, and good crop yield. We can also observe different varieties of datasets that are used by the researchers for the classification of the soil as shown in Table II. These datasets include images of the soil taken from the smartphone, Stereo images, Hyperspectral bands, Satellite images, Remote sensing, and Radar data.

B. Deep Learning Techniques for Soil Classification

From this study, we observed that most of the researchers used varieties of CNN models with a different number of layers for soil classification in their research. A few of them are Deep CNN with Inception-v4, VggNet16, ResNet50 architectures, and the CNN Ensemble model with transfer learning.

Deep Neutral Network, Deep learning with compressed Sensing, Extreme Learning Machine, LSTM, and Gated Recurrent Unit are also used for soil classification as shown in Table III.

TABLE III. DEEP LEARNING ALGORITHMS AND PERFORMANCE

Ref.	Algorithms / Models used	Best Output	Limitations / Future works
[1]	Feed Forward Neural Network, LSTM, Gated Recurrent Unit	Validation loss: 2.1354	Latency to be reduced, data capacity can be improved, sowing time can be predicted
[3]	Nneural networks anddeep learning.	R^2 Value 0.57-0.70	Features can be included. Prediction can be improved.
[4]	4 layers deep CNN model	Accuracy 91.47%	Data can be investigated, Accuracy can be improved
[5]	Deep Neural Network (DNN)	Accuracy 96.89%.	Dataset has to be increased. Fertilizers can be suggested.
[6]	Deep learning and Segmentation model	R^2 Value 0.11-0.48	Efficiency can be improved; it can be extended to 3-dimensional data.
[7]	CNN Ensemble with transfer learning.	Accuracy 96.05%	More ensemble methods can be explored.
[8]	CNN	Accuracy: 86%	Features can be adjusted, and the dataset can be increased.
[11]	Extreme Learning Machine (ELM)	Accuracy 90%.	Can be extended to other nutrients with fast ELMs.
[12]	deep CNN, ResNet50, Inception V4, VggNet16	Accuracy: 98.72 %	Accuracy can be improved with different Deep networks and datasets.
[13]	deep learning with Compressed Sensing.	Log_{10}MS E: 1.3	Recovery time can be improved.
[14]	Multi-class Support Vector Machine	Accuracy 91.37%	Deep Learning can be used, Accuracy can be improved
[15]	Random Forest and CNN	R^2value: 0.97–0.98	It can be extended for onsite soil texture prediction.
[17]	CNN and Support Vector Machine	Accuracy 95%	Accuracy can be improved
[21]	deep CNN	RMSE 9.9%	Accuracy can be improved
[23]	deep CNN	Accuracy 97%	More data can be generated, it can be tested on real data.
[24]	Deep CNN	Accuracy 72% Avg	Dataset can be enhanced; Accuracy can be improved

Deep learning techniques are performing more accurately because a large amount of data can be fed to the system for better results. As these techniques are producing good results for the images of a variety of sources, they are more comfortable for the development of the classification models.

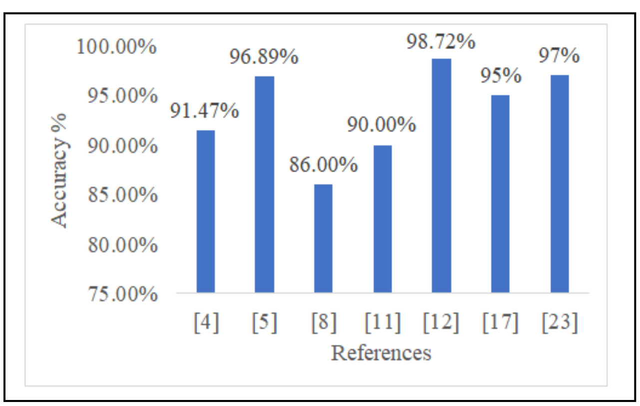

Fig. 7. Performance of deep learning techniques for Soil Classification

The performance of a few deep learning-based approaches for soil classification according to the study is shown in Fig. 7. It is observed that using deep learning techniques the performances are good as 90% and above except for reference [8] (as they have used a small dataset). It is also observed that performance can further be improved by overcoming the limitations, using advanced deep learning techniques, reducing process time with high-speed systems, and increasing the dataset with additional features as well.

C. Our Contribution to this Study

After studying the above publications and noting the performances and limitations of the research going on in the area of soil classification, it is observed that we can further improve the research. By considering all three varieties of soil parameters together, we can perform precise analysis and classification of the soil to find out its suitability for growing particular types of crops. Hence a novel method of soil classification using deep learning that uses all varieties of soil features is proposed as shown in Fig. 8. It will be more helpful to the farmers to select suitable crops to be cultivated for better yielding.

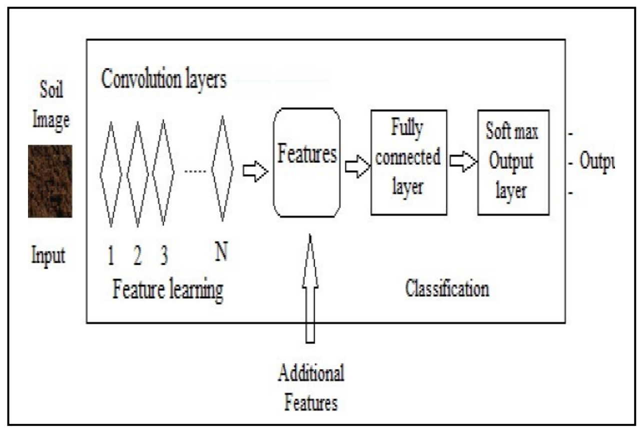

Fig. 8. Proposed deep CNN Architecture for Soil Classification

In the proposed system, along with the physical parameters of the soil, we can include soil nutrients and environmental parameters, etc. as additional features, to be considered for precise classification of the soil.

V. CONCLUSION

Agriculture will be one of the most important sectors in the future. The application of deep learning is promising with its good results and is very much required to enhance the production of crops. Sustainable soil health management is very much required in low-quality soils so that the quality and nutrients of the soil are maintained for good yielding of the crop. This paper studied various deep learning techniques implemented for soil classification for the last five years. The performance and limitations of different algorithms along with varieties of datasets and soil parameters were analyzed and tabulated. The performances based on accuracy were compared and depicted graphically. To overcome the limitations and improve the performance, a novel deep learning model for soil classification was proposed.

In this model, we can consider all varieties of soil parameters for precise classification of the soil. In our future work, we want to implement our proposed system on the real-time dataset. We can overcome the limitations by using high-speed systems and massive data and achieve superior performance. We believe that this study paper will flagstone the way for further research in soil classification.

ACKNOWLEDGMENT

We thank VIT-AP University for providing facilities to perform our research work.

REFERENCES

[1] S. Aruul Mozhi Varman, Arvind Ram Baskaran, S. Aravindh, and E. Prabhu, "Deep learning and IoT for smart agriculture using WSN," in *2017 IEEE International Conference on Computational Intelligence and Computing Research (ICCIC)*, pp. 1-6. IEEE, 2017.

[2] Andreas Kamilaris, and Francesc X. Prenafeta-Boldú, "Deep learning in agriculture: A survey," *Computers and electronics in agriculture* 147 (2018): 70-90.

[3] M.S. Sirsat, Eva Cernadas, M. Fernández-Delgado, and Senén Barro, "Automatic prediction of village-wise soil fertility for several nutrients in India using a wide range of regression methods," *Computers and electronics in agriculture* 154 (2018): 120-133.

[4] Yan Lu, Daniel Perez, Minh Dao, Chiman Kwan, and Jiang Li, "Deep learning with synthetic hyperspectral images for improved soil detection in multispectral imagery," in *2018 9th IEEE annual ubiquitous computing, Electronics & Mobile Communication Conference (UEMCON)*, pp. 666-672. IEEE, 2018.

[5] P. Kanaga Priya and N. Yuvaraj, "An IoT based gradient descent approach for precision crop suggestion using MLP," in *Journal of Physics: Conference Series*, vol. 1362, no. 1, p. 012038. IOP Publishing, 2019.

[6] Wen Dong, Yingwei Sun, and Jiancheng Lu, "Fine mapping of key soil nutrient content using high resolution remote sensing image to support precision agriculture in Northwest China," in *2019 8th International Conference on Agro-Geoinformatics (Agro-Geoinformatics)*, pp. 1-5. IEEE, 2019.

[7] Yushi Chen, Ying Wang, Yanfeng Gu, Xin He, Pedram Ghamisi, and Xiuping Jia, "Deep learning ensemble for hyperspectral image classification," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 12, no. 6 (2019): 1882-1897.

[8] Shinya Inazumi, Sutasinee Intui, Apiniti Jotisankasa, Susit Chaiprakaikeow, and Kazuhiko Kojima, "Artificial intelligence system for supporting soil classification," *Results in Engineering* 8 (2020): 100188.

[9] Thomas van Klompenburga, Ayalew Kassahun, and Cagatay Catal, "Crop yield prediction using machine learning: A systematic literature review," *Computers and Electronics in Agriculture* 177 (2020): 105709.

[10] Krupa Patel and Hiren B. Patel, "A state-of-the-art survey on recommendation system and prospective extensions," *Computers and Electronics in Agriculture* 178 (2020): 105779.

[11] M.S. Suchitra and Maya L. Pai, "Improving the prediction accuracy of soil nutrient classification by optimizing extreme learning machine parameters," *Information processing in Agriculture* 7, no. 1 (2020): 72-82.

[12] Afshin Azizi, Yousef Abbaspour Gilandeh, Tarahom Mesri-Gundoshmian, Ali Akbar Saleh-Bigdeli, and Hamid Abrishami Moghaddam, "Classification of soil aggregates: A novel approach based on deep learning," *Soil and Tillage Research* 199 (2020): 104586.

[13] Jie Ren, Jing Liang, and Yuanyuan Zhao, "Soil ph measurement based on compressive sensing and deep image prior," *IEEE Transactions on Emerging Topics in Computational Intelligence* 4, no. 1 (2020): 74-82.

[14] Utpal Barman and Ridip Dev Choudhury, "Soil texture classification using multi class support vector machine," *Information processing in agriculture* 7, no. 2 (2020): 318-332.

[15] R.K. Swetha, Prajwal Bende, Kabeer Singh, Srikanth Gorthi, Asim Biswas, Bin Li, David C. Weindorf, and Somsubhra Chakraborty, "Predicting soil texture from smartphone-captured digital images and an applicatio," *Geoderma* 376 (2020): 114562.

[16] P. Kuppusamy, S. Venkatraman, C. Rishikeshan, and Y. Padmanabha Reddy, "Deep learning based energy efficient optimal timetable rescheduling model for intelligent metro transportation systems Phys. Commun. 42, 101131," (2020).

[17] Xueying Li, Pingping Fan, Zongmin Li, Guangyuan Chen, Huimin Qiu, and Guangli Hou, "Soil classification based on deep learning algorithm and visible near-infrared spectroscopy," *Journal of Spectroscopy* 2021 (2021).

[18] Pallavi Srivastava, Aasheesh Shukla, and Atul Bansal, "A comprehensive review on soil classification using deep learning and computer vision techniques," *Multimedia Tools and Applications* 80, no. 10 (2021): 14887-14914.

[19] Lefteris Benos, Aristotelis C. Tagarakis, Georgios Dolias, Remigio Berruto, Dimitrios Kateris, and Dionysis Bochtis, "Machine learning in agriculture: A comprehensive updated review," *Sensors* 21, no. 11 (2021): 3758.

[20] Priyadharshini A, Swapneel Chakraborty, Aayush Kumar, and Omen Rajendra Pooniwala, "Intelligent Crop Recommendation System using Machine Learning," in *2021 5th International Conference on Computing Methodologies and Communication (ICCMC)*, pp. 843-848. IEEE, 2021.

[21] Blaž Pongrac and Dušan Gleich, "Regression Neural Network for Soil Moisture Estimation," in *2021 7th Asia-Pacific Conference on Synthetic Aperture Radar (APSAR)*, pp. 1-4. IEEE, 2021.

[22] Vikas Khullar, Sachin Ahuja, Rai Gaurang Tiwar, and Ambuj Kumar Agarwa, "Investigating Efficacy of Deep Trained Soil Classification System with Augmented Data," in *2021 9th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions)(ICRITO)*, pp. 1-5. IEEE, 2021.

[23] Nairit Barkataki, Sharmistha Mazumdar, P. Bipasha Devi Singha, Jyoti Kumari, Banty Tiru, and Utpal Sarma, "Classification of soil types from GPR B scans using deep learning techniques," in *2021 International Conference on Recent Trends on Electronics, Information, Communication & Technology (RTEICT)*, pp. 840-844. IEEE, 2021.

[24] Abhinav Pandey, Devesh Kumar, and Debarati B. Chakraborty, "Soil Type Classification from High Resolution Satellite Images with Deep CNN," in *2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS*, pp. 4087-4090. IEEE, 2021.

[25] P. Kuppusamy and Che-Lun Hung, "Enriching the Multi-Object Detection using Convolutional Neural Network in Macro-Image," in *2021 International Conference on Computer Communication and Informatics (ICCCI)*, pp. 1-5. IEEE, 2021.