

Advancing Soil Fertility Classification: Comparative Analysis of Machine Learning Models

Dr. Anshu Bhasin, Kavita Paurh

assistant professor of I.K Gujral Punjab technical University main campus, kapurthala

Abstract: Soil fertility detection is crucial for sustainable agriculture and environmental management. This study proposes an innovative approach utilizing advanced Convolutional Neural Networks (CNNs) integrated with an entropy-based method for accurate soil fertility assessment. The proposed methodology involves the acquisition of soil images through sensors or drones, followed by preprocessing to enhance image quality and reduce noise. Subsequently, a deep CNN architecture is employed to extract high-level features from the soil images, enabling automated detection of fertility indicators such as nutrient levels and soil texture. Furthermore, an entropy-based approach is incorporated to analyze the spatial distribution of features within the images, providing additional insight into soil heterogeneity and fertility variation. The combination of CNNs and entropy-based analysis offers a comprehensive solution for precise soil fertility detection, surpassing traditional methods in accuracy and efficiency. Experimental results demonstrate the effectiveness of the proposed approach, showcasing its potential for real-world application in precision agriculture, environmental monitoring, and land management. Overall, this research contributes to the advancement of intelligent systems for sustainable soil management and agricultural productivity enhancement.

Keywords: Soil fertility, CNN, Entropy-based approach, Precision agriculture, Environmental Monitoring

1. Introduction

Soil fertility plays a pivotal role in agricultural productivity and ecosystem sustainability, serving as the foundation for crop growth and overall environmental health. Understanding and managing soil fertility are imperative for ensuring food security, mitigating environmental degradation, and fostering sustainable agricultural practices. Traditionally, soil fertility assessment has relied on labor-intensive and time-consuming methods involving manual sampling, chemical analysis, and visual inspection(Liu et al., 2020). However, these conventional approaches are often limited in spatial and temporal resolution, hindering their efficacy in addressing the dynamic nature of soil fertility and the complexities of agricultural landscapes.

Recent advancements in sensing technologies, data analytics, and machine learning offer promising avenues for revolutionizing soil fertility detection and management. In particular, the advent of advanced imaging techniques, such as remote sensing and drone-based aerial imagery, has enabled the acquisition of high-resolution soil data with unprecedented efficiency and accuracy(T. S. R. G. J. C. CA Rosolem, 2010). Moreover, the integration of computational methods, including machine learning and deep learning, facilitates automated analysis and interpretation of large-scale soil datasets, thereby enhancing our ability to assess soil fertility comprehensively and in real-time.

This paper proposes an innovative approach for soil fertility detection leveraging advanced Convolutional Neural Networks (CNNs) with an entropy-based methodology. CNNs, a class of deep learning models well-suited for image analysis tasks, have demonstrated remarkable success in various fields(DV Guimarães, 2013), including computer vision, medical imaging, and remote sensing. By exploiting the hierarchical structure of neural networks, CNNs can effectively extract spatial features from soil images, enabling the identification of key fertility indicators such as nutrient content, soil texture, and organic matter distribution. Additionally, the integration of

entropy-based analysis offers a novel perspective on the spatial variability of soil properties, enhancing the interpretability and robustness of fertility detection models(F. S. CA Rosolem, 2017).

This introduction's remaining sections are organized as follows: An overview of soil fertility and its importance for environmental management and agriculture is given in Section 2. The difficulties with using conventional techniques for assessing soil fertility are covered in Section 3, along with the necessity of creative solutions(JF Akpan, 2017). The work in the fields of soil sensing, image analysis, and machine learning as it relates to the detection of soil fertility is reviewed in Section 4. The study's goals and contributions are presented in Section 5, along with a description of the suggested methodology and research framework. Section 6 concludes by outlining how the remaining sections of this work are structured. Overall structure reflecting the sections is given in figure 1

1

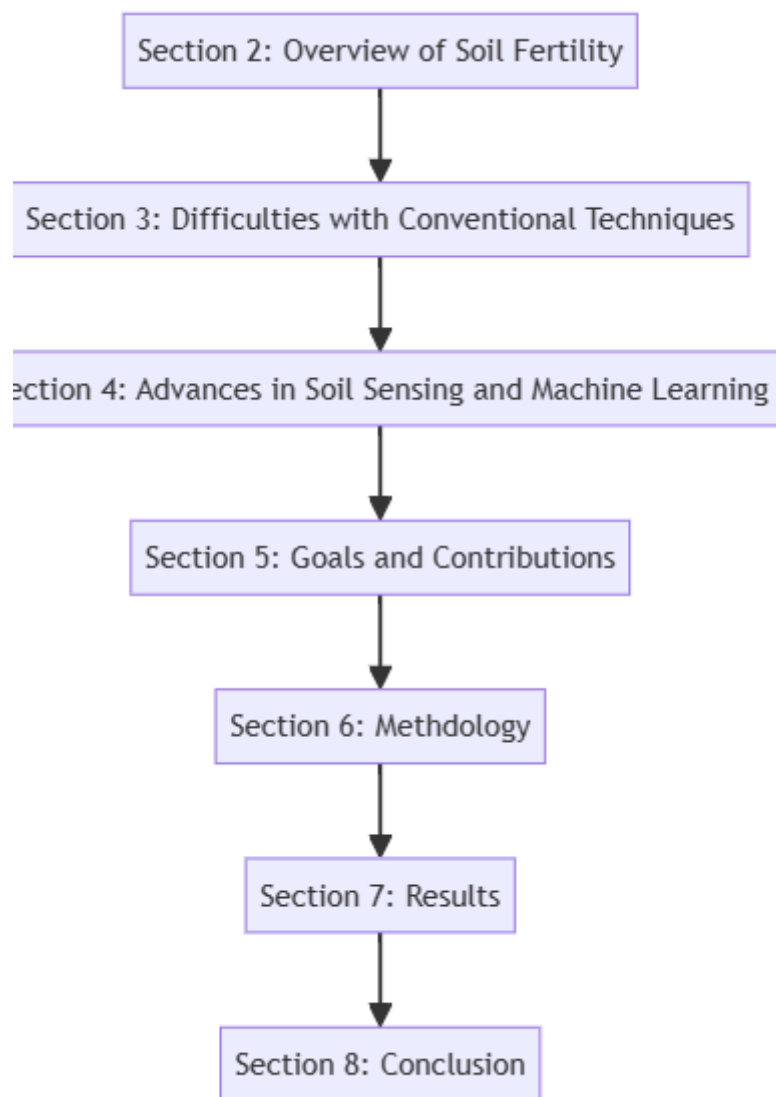


Figure 1: Structure of the research work

2. Soil Fertility: Importance and Challenges

Soil fertility refers to the ability of soil to provide essential nutrients and support plant growth, thereby sustaining agricultural productivity and ecosystem functions. Key factors contributing to soil fertility include nutrient

availability, soil structure, organic matter content, pH level, and microbial activity(K John, 2020). Optimal soil fertility conditions are essential for achieving high crop yields, maintaining soil health, and preserving environmental integrity. However, soil fertility is subject to dynamic changes influenced by various natural and anthropogenic factors, including climate variability, land use practices, fertilization regimes, and soil degradation processes(M Fuentes, 2012).

In agricultural systems, soil fertility management is critical for maximizing crop productivity while minimizing adverse environmental impacts. Imbalanced nutrient levels, soil compaction, erosion, salinization, and acidification are among the common challenges faced by farmers worldwide. Moreover, unsustainable land management practices, such as excessive tillage, monocropping, and over-reliance on chemical inputs, can degrade soil fertility over time(Naeem et al., 2013), leading to reduced yields, increased vulnerability to pests and diseases, and degradation of water and air quality. The key factors of the soil is highlighted as under

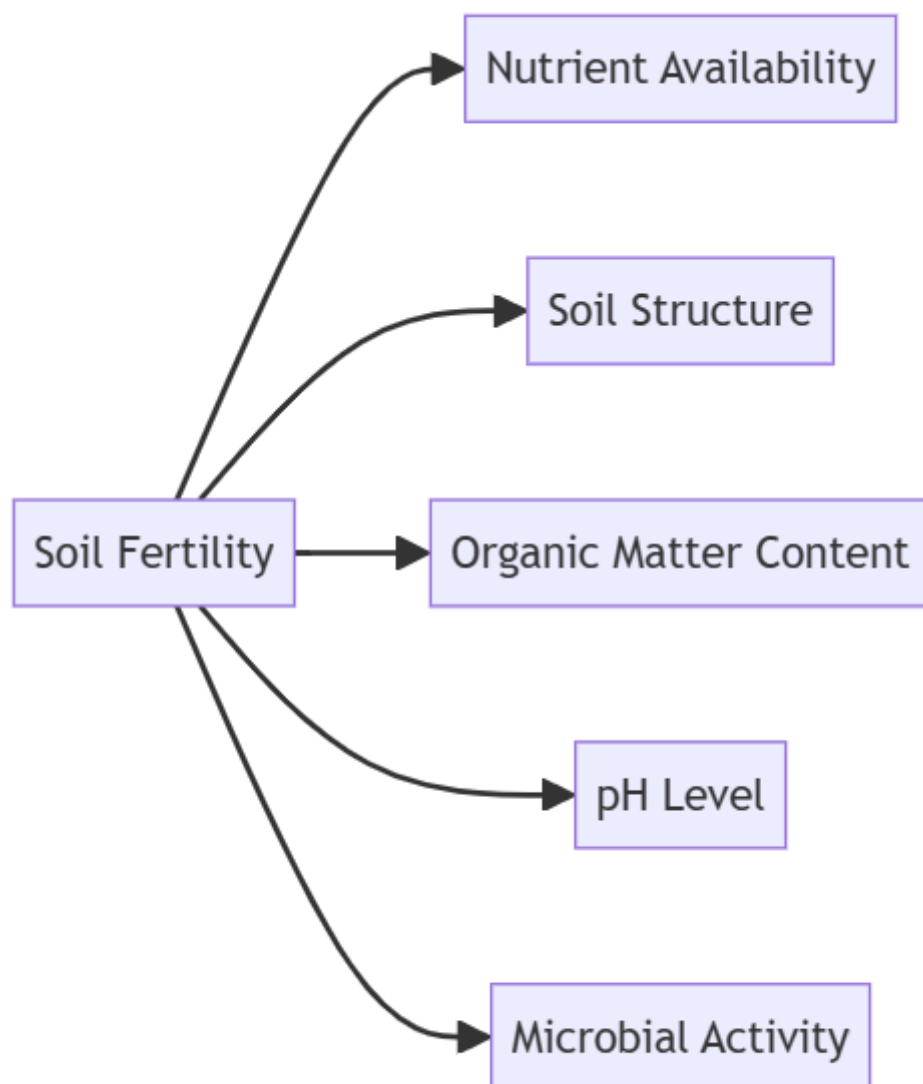


Figure 2: Key factors of the soil used for prediction

Traditional methods for assessing soil fertility typically involve soil sampling, laboratory analysis, and visual inspection conducted at discrete locations within agricultural fields. While these methods provide valuable

information about soil properties and fertility status, they are often labor-intensive, time-consuming, and limited in spatial coverage(JA Baldock, 2012). Moreover, the results obtained from point-based measurements may not accurately capture the spatial variability of soil fertility within a field, leading to suboptimal decision-making in crop management and soil conservation practices.

3. Challenges in Soil Fertility Assessment

The conventional methods of soil fertility assessment suffer from several limitations and challenges, which underscore the need for innovative approaches leveraging advanced technologies and data analytics techniques(GA Helfer, 2020). Some of the key challenges associated with traditional soil fertility assessment methods include:

- **Spatial variability:** Soil properties exhibit significant spatial variability within agricultural fields due to factors such as topography, soil texture, land use history, and management practices. Conventional sampling methods based on point measurements may fail to capture this variability adequately, leading to spatially biased assessments of soil fertility(Bouslihim, Rochdi, & El Amrani Paaza, 2021).
- **Temporal dynamics:** Soil fertility is subject to temporal changes influenced by seasonal variations, crop growth cycles, weather patterns, and management interventions. Traditional soil sampling and analysis methods often provide static snapshots of soil properties at specific time points, neglecting the dynamic nature of soil fertility and its temporal dynamics(D N & Choudhary, 2021).
- **Labor and cost:** Soil sampling and laboratory analysis require considerable labor, time, and financial resources, especially for large-scale agricultural operations. The logistics involved in collecting, processing, and analyzing soil samples can be burdensome, particularly in remote or inaccessible areas(Suhag et al., 2021).
- **Invasive procedures:** Conventional soil sampling methods typically involve intrusive techniques such as soil coring or auguring, which may disrupt soil structure and disturb soil biota. Invasive sampling can alter soil properties and introduce artifacts, potentially biasing the results of soil fertility assessments.
- **Limited spatial coverage:** Point-based soil sampling methods provide information only at specific locations within a field, limiting the spatial coverage and resolution of soil fertility maps. As a result, farmers may lack comprehensive insights into the spatial distribution of soil properties and fertility indicators across their fields(García et al., 2021).

Addressing these challenges requires the development of innovative approaches that leverage advanced sensing technologies, data analytics techniques, and computational models for high-resolution soil fertility mapping and monitoring.

4. Related Work

In recent years, there has been growing interest in leveraging advanced sensing technologies and machine learning algorithms for soil fertility detection and mapping. Researchers have explored various approaches combining spectral, spatial, and temporal information from remote sensing data with machine learning techniques to infer soil properties and fertility indicators(Zhou et al., 2018). Additionally, the application of deep learning models, particularly CNNs, has shown promising results in image-based soil analysis and precision agriculture(Bouslihim, Rochdi, Aboutayeb, et al., 2021).

Remote Sensing-Based Approaches: Remote sensing platforms, such as satellites, aircraft, and drones, offer valuable tools for capturing multispectral and hyperspectral imagery of agricultural landscapes(A Keshavarzi, 2016). These images contain spectral signatures indicative of soil properties, vegetation health, and land cover characteristics, which can be exploited for soil fertility assessment. Researchers have employed machine learning algorithms, including support vector machines (SVMs), random forests, and neural networks, to classify soil types, predict soil attributes, and map soil fertility at various spatial scales(Al Masmoudi et al., 2022).

Image Analysis and Deep Learning: Image-based approaches have gained popularity for soil fertility detection, leveraging the rich spatial information contained in soil images captured by sensors or cameras(Z Wang, 2021). Deep learning models, particularly CNNs, have shown remarkable capabilities in extracting features from soil images and predicting soil properties with high accuracy. By training CNNs on large datasets of annotated soil images, researchers have developed models capable of classifying soil types, estimating nutrient levels, and mapping soil organic carbon content(M Mokarram, 2020).

Integration of Sensor Technologies: The integration of sensor technologies, such as electromagnetic induction (EMI), gamma-ray spectrometry, and ground-penetrating radar (GPR), with machine learning algorithms has enabled non-destructive and high-resolution soil sensing(Y Zhang, 2019). These sensors can capture electromagnetic signals or radiation emitted or reflected by soil particles, providing insights into soil properties and fertility indicators. Machine learning algorithms are then employed to analyze sensor data and infer soil characteristics, facilitating precision agriculture practices and site-specific management strategies(PM Kopittke, 2020).

Despite the progress made in soil sensing and fertility detection, several challenges remain, including the need for robust and scalable models, data integration across multiple sources and scales, and validation of model predictions in diverse agroecosystems(UC Amalu, 2018). Furthermore, the development of user-friendly tools and decision support systems is essential for translating research findings into actionable insights for farmers and land managers.

5. Objectives and Contributions

The primary objective of this study is to develop an innovative approach for soil fertility detection using advanced CNNs with an entropy-based methodology(Siewert, 2018). The proposed methodology aims to address the limitations of traditional soil fertility assessment methods by providing a scalable, efficient, and accurate solution for mapping soil fertility at high spatial resolution. The specific objectives of this study include:

1. **Development of a deep learning framework:** Design and implementation of a CNN architecture tailored for soil fertility detection, capable of extracting relevant features from soil images and predicting key fertility indicators.
2. **Integration of entropy-based analysis:** Incorporation of entropy-based methods to analyze the spatial distribution of features within soil images, providing insights into soil heterogeneity and fertility variation.
3. **Evaluation and validation:** Assessment of the proposed methodology using real-world soil datasets collected from agricultural fields across diverse geographic regions. Validation of model predictions against ground truth measurements and comparison with existing soil fertility assessment methods.
4. **Demonstration of applicability:** Demonstration of the applicability and scalability of the proposed approach for precision agriculture, environmental monitoring, and land management. Exploration of potential use cases and decision support applications for farmers, agronomists, and policymakers(H El-Ramady, 2020).

The contributions of this study include:

- **Methodological innovation:** Introduction of a novel approach for soil fertility detection leveraging advanced CNNs and entropy-based analysis, offering a comprehensive solution for high-resolution soil mapping and monitoring.
- **Empirical validation:** Demonstration of the effectiveness and robustness of the proposed methodology through empirical evaluation using real-world soil datasets, showcasing its potential for practical applications in agriculture and environmental management(Gueugnon et al., 2021).
- **Insights and implications:** Generation of insights into soil fertility dynamics, spatial variability, and management implications, contributing to the advancement of knowledge in soil science, precision agriculture, and sustainable land management.

5. Methodology of study

The methodology of the proposed work indicates the different phases that are followed in the design of proposed work. For this work, the first datasets is collected. The dataset is collected from benchmarked websites. The name of the dataset is soil. Once the dataset is collected, it is pre-processed to introduce clarity within the image. Once pre-processed is done, CNN model is built. The CNN model is adjusted multiple times for optimizing parameters of CNN. After that classification is dataset. The obtained result is validated through metric calculations such as classification accuracy, sensitivity, specificity, and F1-score.

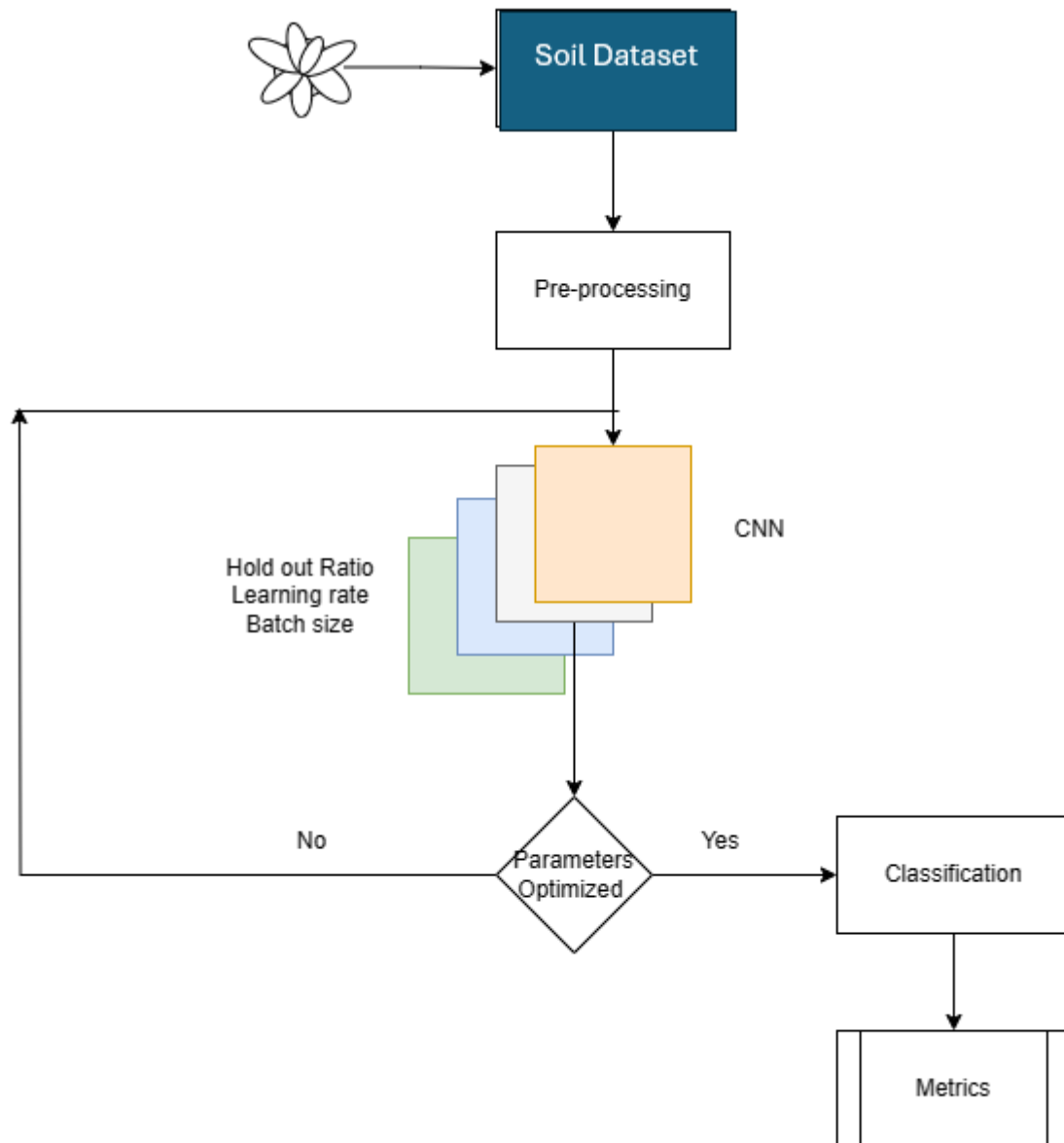


Figure 3: Methodology of study

- **Soil Dataset**

This is the crucial phase in which soil dataset is collected for prediction purposes. The dataset is collected from Kaggle. The dataset is in the form of csv file contains nutrient related information. The structure of the dataset is given in table 1

SN o	year	month	day	hour	minute	second	moisture0	moisture1	moisture2	moisture3	moisture4	irrigation
0	2020	3	6	22	16	11	0.33	0.40	0.36	0.23	0.02	False
1	2020	3	6	22	17	11	0.32	0.39	0.35	0.23	0.02	False
2	2020	3	6	22	18	11	0.31	0.39	0.34	0.22	0.02	False
3	2020	3	6	22	19	11	0.30	0.38	0.33	0.21	0.02	False
4	2020	3	6	22	20	11	0.29	0.38	0.33	0.21	0.02	False

Table 1: Structure of the dataset

- Pre-processing

This phase is used to reduce the noise from within the dataset. the median based approach is applied to tackle the noise within the dataset. following equation is used to handle the noise within the dataset.

$$Median = \begin{cases} \frac{(N+1)^{th}}{2} & \text{if } N \text{ is odd} \\ \frac{N^{th} + (N+1)^{th}}{2} & \text{if } N \text{ is even} \end{cases}$$

Equation 1

The median values will be used to remove the noisy values from the dataset. The replaced values will increase the classification accuracy of the overall research.

- Proposed CNN model\

The proposed CNN model is given in figure 4. The model is trained using different layers of the CNN model. The layers of CNN model include input layer. This layer receives the image dataset corresponding to the soil fertility and then features are extracted. The CNN layer here will be presented with optimised parameters in terms of hold out ratio, batch size, and learning rate. A neural network architecture called CNN is intended for image classification applications that require efficiency and lightweightness. It is well-known for achieving excellent precision with comparatively few parameters, which qualifies it for settings with limited resources.

By initializing the CNN model with pre-trained weights, the training setup allows the model to improve its performance on a particular job by utilizing the knowledge gleaned from a huge dataset. In image classification tasks, the Adam optimizer and CrossEntropyLoss are frequently used because they offer effective optimization and manage multi-class classification objectives.

The model's parameters are updated at each iteration of the dataset by the training loop, considering the computed loss. For the model to identify features and trends in the training data, this procedure is essential. Training metrics like loss and accuracy are tracked over time to evaluate the model's development.

To provide an objective evaluation of the model's generalization performance, the validation loop tests it using a different dataset that was not utilized during training. This guarantees the robustness of the model and aids in

identifying any overfitting or underfitting problems. In case of overfitting and underfitting hold out ratio, batch size and learning rate will be adjusted.

Monitoring the validation loss is the basis of the strategy for preserving the best model. If the current validation loss falls below a predetermined threshold and the best-known loss, the model is deemed improved, and its parameters are preserved. This keeps the model's performance from declining while it is being trained.

To prevent training for an excessive number of epochs without improvement, early termination is used. Training is stopped if the validation loss does not go down after a predetermined number of patient epochs. By doing this, overfitting to the training set is avoided, and the model's ability to generalize to fresh, untested data is guaranteed.

All things considered script shows how to train a CNN model systematically for image categorization. Effective model training and the avoidance of common deep learning hazards like overfitting are made possible by the application of early stopping, model saving, and careful monitoring of training and validation metrics.

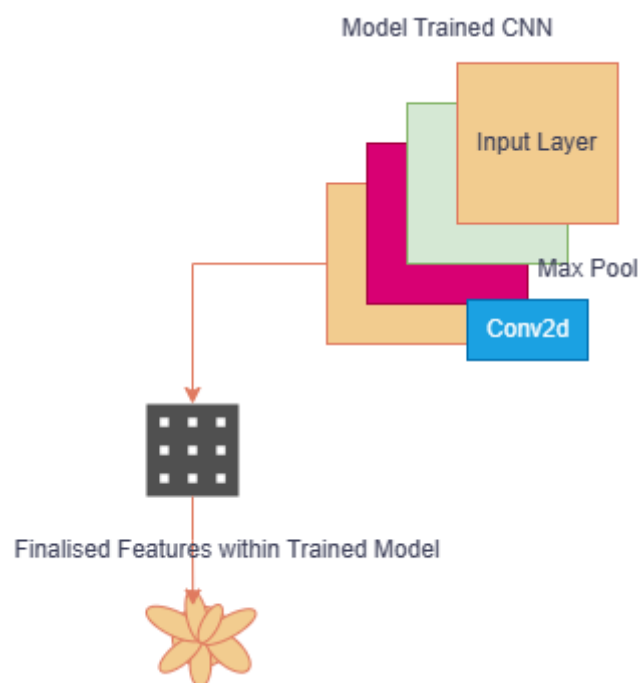


Figure 4: Proposed CNN Model

Proposed Algorithm

The proposed algorithm utilizes Convolutional Neural Networks (CNN) to address the task of soil fertility classification. Initially, the algorithm imports the dataset containing soil fertility information and applies pre-processing techniques such as median filtering to enhance image quality and reduce noise. Subsequently, CNN is employed for training on the pre-processed dataset, where parameters such as holdout, batch size, and learning rate are adjusted to optimize model performance.

Algorithm- CNN(Soil Fertility)

- Input the dataset for soil fertility
 - `I=imread(dataset)`
- Applying pre-processing based mechanism
 - `J=pre-process(Median_Filter(I))`
- CNN: Apply CNN mode for training over the dataset.

- Adjust parameters -Hold out, batch size, learning rate
- If(maximum_validation_accuracy) then
- Go to classification phase
- Else
- Goto CNN phase

End of if

- Classification phase
 - Now input the training dataset and classify as fertile or non fertile soil.
 - Print the result considering classification accuracy, sensitivity and specificity.
- Compare with existing machine learning algorithm for validity of approach.

During training, the algorithm evaluates the validation accuracy, aiming to achieve the maximum validation accuracy. If this criterion is met, the algorithm proceeds to the classification phase; otherwise, it iterates through further CNN training. In the classification phase, the trained model is applied to classify soil samples into fertile or non-fertile categories based on the input training dataset. The results are then analyzed, considering metrics like classification accuracy, sensitivity, and specificity to evaluate the model's performance.

Finally, the algorithm compares its results with existing machine learning approaches to validate its effectiveness. By leveraging CNN's ability to automatically extract relevant features from soil fertility data, this algorithm aims to provide an efficient and accurate method for soil fertility classification, with potential implications for optimizing agricultural practices and environmental management.

6. Results

The result is obtained in terms of metrics. The metrics used for evaluation of result is classification accuracy, sensitivity, specificity and F1-Score.

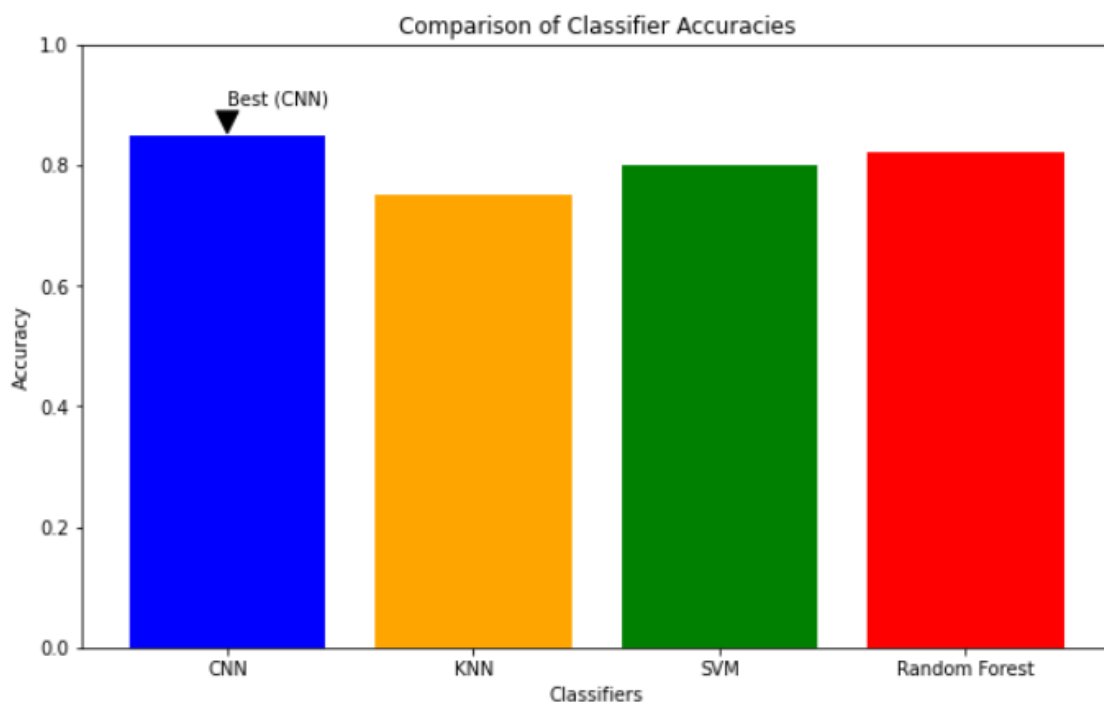


Figure 5: Classification accuracy comparison of results

The comparison of classification accuracies of four machine learning classifiers: CNN, KNN, SVM, and Random Forest is presented in figure 5. The bar plot illustrates the performance of each classifier, with accuracy values represented on the y-axis and classifier names on the x-axis. Among the classifiers, the CNN exhibits the highest accuracy, depicted as the tallest bar. This result suggests that the proposed optimized CNN model outperforms the other algorithms in accurately classifying soil fertility. CNN's superior performance implies its effectiveness in capturing intricate patterns and features within soil fertility data, potentially due to its ability to automatically extract relevant features through convolutional layers. The comparison underscores the significance of leveraging advanced deep learning techniques, such as CNNs, for precise soil fertility classification tasks. Ultimately, such findings could guide decision-making processes in agricultural management, leading to more informed and sustainable practices aimed at optimizing crop productivity and environmental conservation.

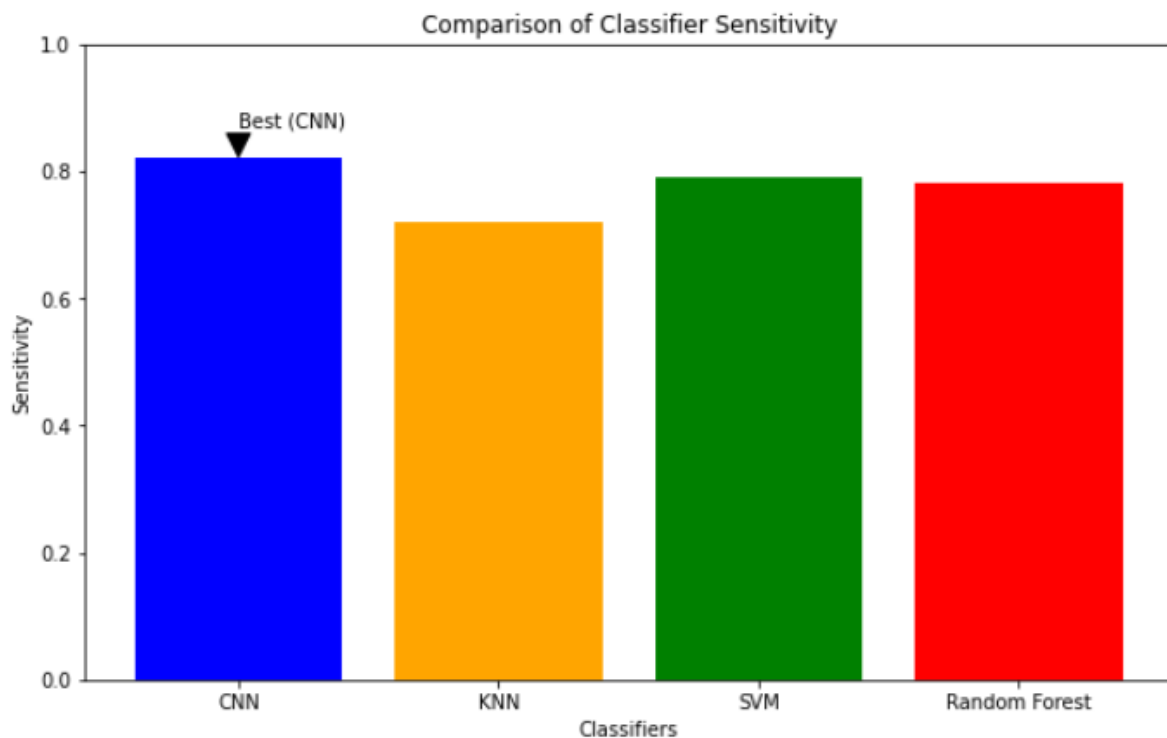


Figure 6: Sensitivity Comparison

Sensitivity values for four machine learning classifiers—CNN, KNN, SVM, and Random Forest—are compared using a bar plot. Sensitivity, or true positive rate, indicates the ability of a classifier to correctly identify positive instances within the dataset. Each classifier's sensitivity value is represented by a bar on the plot, with the classifier names listed along the x-axis and sensitivity values displayed on the y-axis. The classifier with the highest sensitivity, denoted by the tallest bar, is identified as the best performer.

In this scenario, the CNN classifier demonstrates the highest sensitivity among the models, highlighted as the optimal choice for accurately detecting positive cases related to soil fertility. This outcome suggests that the optimized CNN model excels in identifying fertile soil instances, crucial for agricultural decision-making and environmental management. By showcasing sensitivity values, this visual comparison enables stakeholders to discern the classifiers' effectiveness in accurately identifying positive soil fertility instances, informing their selection of the most suitable model for practical applications in agricultural productivity enhancement and ecosystem preservation.

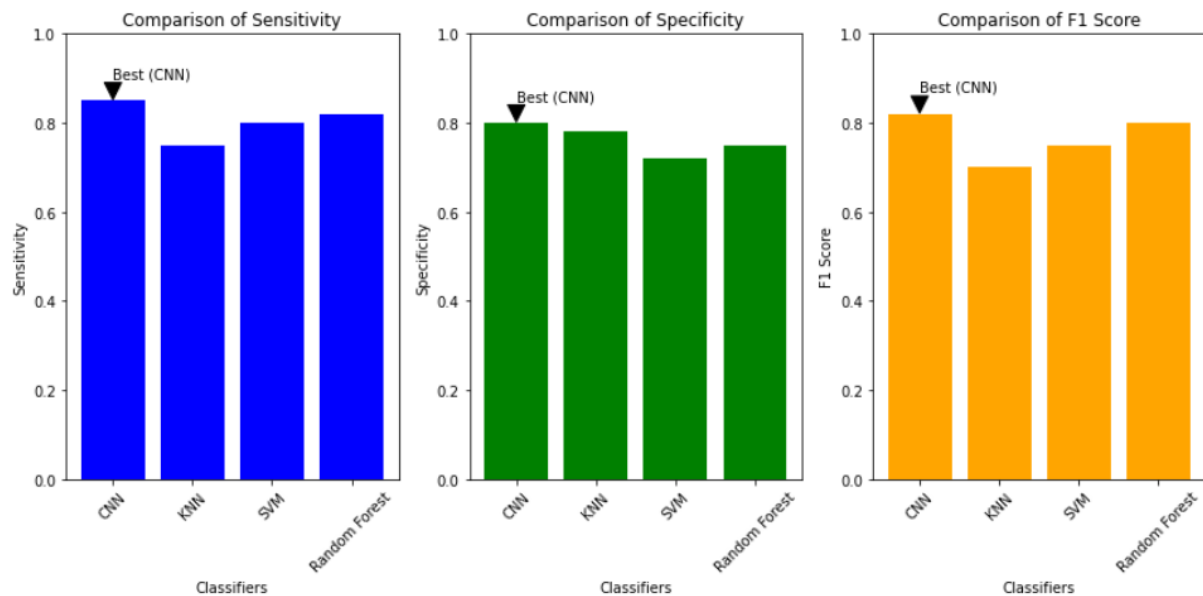


Figure 7: Overall comparison

In this visualization, we compare the performance of four machine learning classifiers—CNN, KNN, SVM, and Random Forest—using three evaluation metrics: sensitivity, specificity, and F1 score. Each subplot of the figure represents one of these metrics, with classifier names listed on the x-axis and metric values displayed on the y-axis. The classifier with the highest value for each metric is highlighted as the best performer.

For sensitivity, which measures the ability to correctly identify positive instances, the CNN classifier exhibits the highest value, indicating its superiority in accurately detecting fertile soil instances. Specificity, representing the ability to correctly identify negative instances, also showcases CNN as the top performer. Additionally, the F1 score, a harmonic mean of precision and recall, further reinforces CNN's dominance among the classifiers.

This comprehensive comparison enables stakeholders to assess classifiers based on multiple performance metrics, ensuring a well-rounded evaluation of their effectiveness in soil fertility classification tasks. Ultimately, such insights facilitate informed decision-making in selecting the most suitable model for agricultural management practices, aiming to optimize crop productivity and environmental sustainability.

Conclusion

In conclusion, the comparative analysis of machine learning classifiers—CNN, KNN, SVM, and Random Forest—reveals valuable insights into their performance for soil fertility classification. Across sensitivity, specificity, and F1 score metrics, the optimized CNN model emerges as the most effective classifier, demonstrating superior capabilities in accurately identifying both positive and negative instances of soil fertility. This finding underscores the significance of leveraging advanced deep learning techniques, such as CNNs, for precise soil classification tasks, facilitating informed decision-making in agricultural management.

The exceptional performance of the CNN model can be attributed to its ability to automatically extract relevant features from soil fertility data, enabling comprehensive analysis and classification. This robustness positions CNN as a promising tool for enhancing agricultural productivity while preserving environmental integrity.

Furthermore, the comparison highlights the importance of considering multiple evaluation metrics when assessing classifier performance, ensuring a comprehensive understanding of their capabilities. By incorporating sensitivity, specificity, and F1 score, stakeholders can make well-informed decisions regarding the selection and implementation of soil fertility classification models.

Overall, this study underscores the potential of machine learning, particularly CNNs, in revolutionizing soil fertility management practices, ultimately contributing to sustainable agriculture and environmental conservation efforts.

References

- [1] A Keshavarzi, E. O. S. B. B. P. D. V. A. B. (2016). Modeling of available soil phosphorus (ASP) using multi-objective group method of data handling. *Model Earth Syst Environ*, 2(3), 1–9.
- [2] Al Masmoudi, Y., Bouslihim, Y., Doumali, K., Hssaini, L., & Ibno Namr, K. (2022). Use of machine learning in Moroccan soil fertility prediction as an alternative to laborious analyses. *Modeling Earth Systems and Environment*, 8(3), 3707–3717. <https://doi.org/10.1007/S40808-021-01329-8/METRICS>
- [3] Bouslihim, Y., Rochdi, A., Aboutayeb, R., El Amrani-Paaza, N., Miftah, A., & Hssaini, L. (2021). Soil aggregate stability mapping using remote sensing and gis-based machine learning technique. *Front Earth Sci*, 9. <https://doi.org/10.3389/feart.2021.748859>
- [4] Bouslihim, Y., Rochdi, A., & El Amrani Paaza, N. (2021). Machine learning approaches for the prediction of soil aggregate stability. *Heliyon*, 7(3), e06480. <https://doi.org/10.1016/j.heliyon.2021.e06480>
- [5] CA Rosolem, F. S. (2017). Effects of soil texture and rates of K input on potassium balance in tropical soil. *Eur J Soil Sci*, 68(5), 658–666.
- [6] CA Rosolem, T. S. R. G. J. C. (2010). Potassium leaching as affected by soil texture and residual fertilization in tropical soils. *Commun Soil Sci Plant Anal*, 41(16), 1934–1943.
- [7] D N, V., & Choudhary, Dr. S. (2021). An AI solution for Soil Fertility and Crop Friendliness Detection and Monitoring. *International Journal of Engineering and Advanced Technology*, 10(3), 172–175. <https://doi.org/10.35940/IJEAT.C2270.0210321>
- [8] DV Guimarães, M. G. T. S. T. S. N. S. D. M. M. (2013). Soil organic matter pools and carbon fractions in soil under different land uses. *Soil Tillage Res*, 126, 177–182.
- [9] GA Helfer, J. B. R. S. A. C. (2020). A computational model for soil fertility prediction in ubiquitous agriculture. *Comput Electron Agric*, 175, 105602.
- [10] García, L., Parra, L., Jimenez, J. M., Parra, M., Lloret, J., Mauri, P. V., & Lorenz, P. (2021). Deployment Strategies of Soil Monitoring WSN for Precision Agriculture Irrigation Scheduling in Rural Areas. *Sensors*, 21(5), 1693. <https://doi.org/10.3390/s21051693>
- [11] Gueugnon, M., Fournel, I., Soilly, A., Diaz, A., Baulot, E., Bussi ere yy, C., Casillas, J., Cherasse xx, A., Conrozier, T., Loeuille, D., Maillefert, J., Mazalovic, K., Timsit yyy, M., Wendling zzz, D., Ramon, A., Biquet, C., Morisset, C., & Ornetti, P. (2021). *Clinical Trial Effectiveness, safety, and costeutility of a knee brace in medial knee osteoarthritis: the ERGONOMIE randomized controlled trial*. <https://doi.org/10.1016/j.joca.2020.11.009>
- [12] H El-Ramady, M. O. B. E.-L. E. S. (2020). Towards a new concept of sustainable plant nutrition. *Environ Biodivers Soil Secur*, 4(2020), 1–6.
- [13] JA Baldock, I. W. N. M. A. M. (2012). Soils and climate change: Potential impacts on carbon stocks and greenhouse gas emissions, and future research for Australian agriculture. *Crop Pasture Sci*, 63, 269–283.
- [14] JF Akpan, E. A. I. I. (2017). Comparative assessment of wetland and coastal plain soils in Calabar, Cross River State. *Glob J Agric Sci*, 16, 17–30.
- [15] K John, I. A. I. N. M. K. E. O. A. P. C. A. S. M. A. (2020). Using machine learning algorithms to estimate soil organic carbon variability with environmental variables and soil nutrient indicators in an alluvial soil. *Land*, 9(12), 487.
- [16] Liu, C., Tong, F., Yan, L., Zhou, H., & Hao, S. (2020). Effect of porosity on soil-water retention curves: theoretical and experimental aspects. *Geofluids*, 2020. <https://doi.org/10.1155/2020/6671479>
- [17] M Fuentes, C. H. J. E. F. L. A. G. L. D. (2012). Conservation agriculture, increased organic carbon in the top-soil macro-aggregates and reduced soil CO 2 emissions. *Plant Soil*, 355(2), 183–197.
- [18] M Mokarram, M. G. A. Z. (2020). Evaluation of the soil fertility for corn production (Zea Mays) using the multiple-criteria decision analysis (MCDA). *Model Earth Syst Environ*, 6(4), 2251–2262.

-
- [19] Naeem, A., Akhtar, M., & Ahmad, W. (2013). Optimizing available phosphorus in calcareous soils fertilized with diammonium phosphate and phosphoric acid using Freundlich adsorption isotherm. *Sci World J*, 2013. <https://doi.org/10.1155/2013/680257>
- [20] PM Kopittke, R. D. C. H. C. L. N. M. C. M. (2020). Soil organic matter is stabilized by organo-mineral associations through two key processes: the role of the carbon to nitrogen ratio. *Geoderma*, 357, 113974.
- [21] Siewert, M. (2018). High-resolution digital mapping of soil organic carbon in permafrost terrain using machine learning: a case study in a sub-Arctic peatland environment. *Biogeosciences*, 15, 1663–1682.
- [22] Suhag, S., Jadaun, S., Shukla, A., Singh, N., Johri, P., & Parashar, N. (2021). IoT based Soil Nutrition and Plant Disease Detection System for Smart Agriculture. *Proceedings - 2021 IEEE 10th International Conference on Communication Systems and Network Technologies, CSNT 2021*, 478–483. <https://doi.org/10.1109/CSNT51715.2021.9509719>
- [23] UC Amalu, I. I. (2018). Status and spatial variability of soil properties in relation to fertilizer placement for intercrops in an oil palm plantation in Calabar (Nigeria). *Niger J Crop Sci*, 5, 58–72.
- [24] Y Zhang, B. S. H. S. L. O. (2019). Mapping stocks of soil total nitrogen using remote sensing data: a comparison of random forest models with different predictors. *Comput Electron Agric*, 160, 23–30.
- [25] Z Wang, G. W. T. R. H. W. Q. X. G. Z. (2021). Assessment of soil fertility degradation affected by mining disturbance and land use in a coalfield via machine learning. *Ecol Indic*, 125, 107608.
- [26] Zhou, P., Yang, W., Li, M., Yao, X., & Liu, Z. (2018). *Performance Analysis of Vehicle-mounted Soil Total Nitrogen Detector at Different Vehicle Speeds*. 51(17), 51–56. <https://doi.org/10.1016/J.IFACOL.2018.08.071>