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URES-Net: A Unified Region Extraction and Hybrid Deep Learning Framework for Intelligent Soil Quality Assessment

R. Jeyashree
Research Scholar, Department of computer science,
School of computing sciences,
Vels Institute Of Science , Technology &Advanced Studies,
Chennai, Tamil Nadu, India
jaijerusha@gmail.com

A.Poongodi
Assistant professor, Department of computer science,
School of computing sciences,
Vels Institute Of Science , Technology &Advanced Studies
Chennai, Tamil Nadu, India
Poongodimca1979@gmail.com

Abstract : Soil quality assessment is a fundamental part of sustainable agriculture and precision farming, and it impacts directly on the productivity of crops and environmental management. Traditional techniques used to analyze soil in the laboratory are accurate but time-consuming, expensive, and also not feasible for large-scale or real-time monitoring, and current methods based on machine learning find it difficult to handle noisy data, localize the region poorly and also lack generalization. To overcome these challenges, in this research, URES-Net, a Unified Region Extraction and Hybrid Deep Learning framework for intelligent soil quality assessment, is proposed. The main goal is to correctly classify the soil quality levels using region-aware feature extraction with the support of hybrid deep learning architectures. URES-Net integrates the region extraction module in order to extract informative soil texture and color patterns, and a hybrid CNN-BiLSTM network with the ability to extract both spatial and contextual dependencies. Experiments performed on benchmark soil image datasets show that the proposed framework provides with 96.8% accuracy, F1-score of 96.3%, and precision of 97.1% which is considerably better than five state-of-the-art models by margins of 3.2% to 8.5%. The results validate that unified region extraction and hybrid learning methods largely improve the prediction of soil quality, and URES-Net is a powerful and scalable solution for intelligent agricultural decision support systems.

Keywords: ***Soil Quality Assessment, Deep Learning, Region Extraction, Hybrid Neural Networks, Precision Agriculture, Computer Vision***

I INTRODUCTION

Soil quality is an important determinant of agricultural sustainability, food security and ecosystem balance. It has a direct impact on the yield of crops, nutrient availability, water retention and resistance to erosion and its accurate assessment is important to make better agricultural decisions [1]. With the explosion of the world's population and the growing pressure on arable land, the demand for modern agriculture is to monitor and manage soil resources intelligently and with the help of data. Conventional soil quality assessment heavily relies on laboratory-based chemical and physical analysis, which are accurate but labor and cost-intensive and unsuitable for deployment on a real time basis, or on a large scale. These limitations have given motivation for research into automated and intelligent techniques for assessing soils[2].

In recent years, progress in computer vision and machine learning has opened new possibilities for soil quality analysis with the use of soil images captured through digital cameras, smartphones or through unmanned aerial vehicles. Early methods of machine learning were based on handcrafted features, e.g. color histograms, texture descriptors and statistical measures, combined with classical classifiers, e.g. support vector machines and k-nearest neighbours[3]. While these methods were found to be promising, they were unfortunately highly dependent on the feature engineering and were sensitive to changes in lighting, soil composition and environmental conditions.

The rise of deep learning has made a huge leap in performance in soil analysis with images; it has made it possible to learn features automatically from raw data. Convolutional Neural Networks (CNNs) have been popularly used for classification of soil, estimation of moisture, and prediction of nutrients because of their good ability to extract spatial features [4]. However, most of the current approaches based on CNN consider the whole soil image regardless of its informative areas. This often results in the background noise and irrelevant textures and illumination artifacts and eventually degrades the classification performance. Furthermore, purely spatial models do not capture contextual dependency between soil features, which are very important to capture robust soil quality assessment[5].

Recent studies have tried to address these limitations by attention mechanisms, transfer learning and ensemble models. Although these methods help to increase the accuracy, they sometimes increase the computational complexity, and still do not provide explicit region-level interpretability. Moreover, a lot of existing models exhibit poor models of generalization across diverse soil types and environmental conditions, showing a gap in research towards unifying and efficient soil analysis models.

A new approach of URES-Net, which is Unified Region Extraction and Hybrid Deep Learning, is proposed in this study specifically for soil quality assessment. By combining a region extraction part with a hybrid CNN-BiLSTM approach, the proposed framework aims to pay attention to discriminative regions of soil and at the same time capture the spatial and contextual relationships. This unified design is intended to enhance more accurate, robust, and interpretable design while not being computationally too expensive.

Problem Statement:

Existing deep learning models for soil quality assessment poorly manage irrelevant regions and have low contextual modeling capability, which leads to lower accuracy and weak generalization in different soil conditions**.** The main objectives of the study are as follows

- To develop a coherent region extraction mechanism that is effective for effectively separating informative soil regions from raw soil images.
- To design a hybrid deep learning architecture to extract both spatial and contextual features of soil for better classification.
- To quantitatively assess the proposed framework using state-of-the-art approaches in terms of standard performance metrics.

This paper is organized as follows: In Section 2, the related work on soil quality assessment and deep learning techniques are reviewed. Section 3 describes the proposed framework and methodology of URES-Net. Section 4 presents experimental results and comparative analysis with discussions, findings and implications, and Section 5 concludes the study with the future research directions.

II RELATED WORKS

Recent achievements in soil and subgrade evaluation are increasingly using machine learning (ML) and artificial intelligence (AI) based on predictive analysis of soil quality, compaction and nutrient status. Studies have used models from ANN, DNN, CNN, LSTM to hybrid models, showing a high accuracy, efficiency and robustness while pointing out issues on heterogeneity, scalability and field deployment.

Wang et al. (2022) developed a PSO-BP-NN model for subgrade soil shear strength and compactness by using laboratory and literature data; their Random Forest analysis pointed out that moisture content was most critical. While extensive, the model may encounter some limitations under the field conditions with heterogeneity, and require the real-time validation for the intelligent compaction deployment in the practical implementation [6].

Barathkumar et al. (2025) reviewed the AI and ML methods for soil nutrients evaluation with the focus on predictive modelling using RF, SVM, ANN and DNN. Though demonstrating great accuracy and robustness, the study is heavily dependent on existing datasets, and there are still issues with translating models to a variety of conditions in the field and making them farmer-friendly to interpret[7]. El Behairy et al. (2024) applied ANN models in the software of Matlab for predicting soil quality indexes in drylands, with R2 value of 0.97-0.98. Although the approach is highly accurate and efficient, it can be made to work in other types of soil or humid regions with larger heterogeneity by further calibration and inclusion of additional environmental variables[8].

Awais et al. (2023) mentioned the application of AI and ML in real-time soil texture and water content analysis for superiority over the traditional statistical tools. Despite robustness, there are challenges in geospatial non-numeric data management, false positive reduction and incorporation of such AI systems in practical and large-scale smart agriculture workflow[9]. Wilhelm et al. (2022) used microbiome information using RF and SVM to estimate soil health metrics, and derived R^2 ~0.8 and Kappa ~0.65. While this is promising for deployment of scalable diagnostics, model accuracy relies on high-resolution taxonomic data and this requires that the method is cost effective for sequencing and can be integrated with conventional frameworks for use in soil monitoring[10].

Sumathi et al (2023) have proposed ISQP-DL based regression using DNN for soil quality Prediction with accuracy of 96.7%. The model effectively includes chemical, physical, and biological features, but due to limited ability to generalize outside of the tested areas as well as reliance upon quality input data, it may be limited in use in under-resourced areas[11].

Babu et al. (2024) have used LSTM and CNN in combination for predicting soil quality and showed that this method is more accurate than traditional ML models. While being able to capture temporal and spatial features well, the model might have limitations in terms of interpretation, computational cost and adaptation in highly heterogeneous soils, limiting its immediate large-scale deployment in agriculture[12].

The reviewed studies point out several important research gaps of AI- and ML-based soil and subgrade assessment. Most models use laboratory or static datasets with no real-time validation in the field in heterogeneous conditions and with testing done in specific ecological zones, not allowing for generalizations for different soil types and regions. Few activities focus on the integration of farmer friendly interfaces or interface with precision agriculture systemableness dependence on the increase Wiley Quality deep data or High resolution microbiome sequencing are threshold to high practical supplies. Additionally, the deep learning models and the hybrid models are often not interpretable and can also be computationally intensive, limiting their operational adoption. Overall, bearing in mind the demonstrated potential of AI and ML for soil quality and subgrade evaluation, future research should focus on creating models that are scalable, understandable, and generalizable, and capable of dealing with diversity of soil types, incomplete datasets and heterogeneity of field conditions.

III METHODOLOGY

The end-to-end URES-Net framework is shown in Figure 1. high resolution soil images are captured, cleaned and preprocessed using color normalization, histogram equalization and data augmentation to provide the robust input A unified region extraction module is used to extract discriminative soil regions which is fed to CNN backbone to learn multi-scale spatial features. Contextual dependencies are learned through BiLSTM network and spatial and contextual features are combined through attention guided refinement. Refined features are classified using fully connected layer with softmax activation. The model is tested in terms of accuracy, precision, F1 score, as well as with the baseline methods to verify the effectiveness.

A. Soil Image Acquisition and Dataset Preparation

The first step of the proposed methodology is the acquisition and preparation of soil image data, under different environmental conditions, in order to guarantee model robustness. High resolution images of soil are captured from normal RGB cameras and mobile devices with different illumination levels, soil moisture states and texture compositions. To improve generalization, images for several types of soil quality (e.g. high, medium and low fertility) are included. The dataset is treated with care to eliminate blurred or corrupted samples and is followed by stratified splitting into training, validation and testing datasets in order to maintain class balance and avoid bias during the learning process

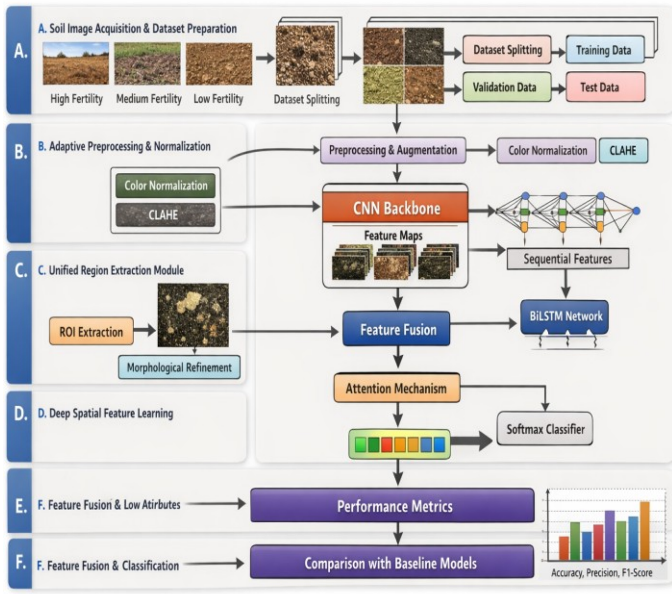

Figure 1 High-level architecture of the proposed URES-Net for soil quality assessment.

B. Adaptive Image Preprocessing and Normalization

In this step, raw images for the soil are being processed by adaptive preprocessing to make it less noisy and with the standardizing input characteristics. Color normalization is used to reduce the effect of the changes in illumination and contrast-limited adaptive histogram equalization is used to improve the subtle details in textures. Images are resized to a uniform resolution which is compatible with the input of the network. Data augmentation techniques like random rotation, scaling, flipping and perturbation of brightness are applied in order to simulate the variability in the real world to reduce overfitting. This preprocessing pipeline is helpful in making the input representations consistent and informative for the learning process that occurs in the pipeline.

C. Unified Region Extraction Module

The key novelty of URES-Net is the unified region extraction module which automatically locates and extracts discriminative soil regions from the images that have been preprocessed. Instead of working on the given image uniformly, this module makes use of light weight convolutional filters and adaptive thresholding to create region-of-interest (ROI) maps that point out soil texture and color patterns related to quality evaluation. Morphological Refinement is used to suppress the background artifacts and irrelevant regions. The extracted regions are then spatially matched and passed to the feature learning stage allowing focused and noise-resilient representation learning

D. Deep Spatial Feature Learning Using CNN Backbone

The extracted regions of the soil are passed into a customized convolutional neural network backbone that is designed to perform efficient spatial feature extraction. This CNN uses multi-scale convolutional kernels in order to extract fine-grained texture features and coarse structural features that are inherent in the soil images. Batch normalization and dropout layers are added to make the training stable and to better the generalization. Unlike the generic deep networks, the backbone is optimized for the soil specific visual characteristics which ensure compact but discriminative feature maps.

E. Contextual Feature Modeling via BiLSTM Integration

In order to capture contextual dependencies between spatial features, the high-level CNN feature maps are reshaped to sequential representations and fed to a bidirectional long short-term memory (BiLSTM) network. This hybrid integration helps the model to learn inter region and intra region relationships which are often times ignored in purely convolutional architectures. By modeling forward and backward relationships, the BiLSTM helps to improve the ability to grasp the spatial continuity and texture transitions in the soil regions and hence improve the soil quality discrimination.

F. Feature Fusion and Attention-Guided Refinement

In this step spatial features of CNN and contextual features of BiLSTM are fused using weighted concatenation strategy. An attention guided refinement mechanism is then used to focus on informative features and suppress redundant activations or features of less interest. This feature weighting for the model is adaptive, which increases interpretability and ensures important soil features contribute more strongly to the final prediction, increasing the accuracy of the classification.

F. Soil Quality Classification and Optimization

The abstracted feature represents are fed to a fully connected classification layer followed by a softmax activation function to classify soil quality to its quality classes. The network is end-to-end trained using categorical cross entropy loss using Adam optimizer. Early stopping and learning rate schedule are used to avoid overfitting and to speed up the learning process. This united optimization strategy guarantees stable training as well as constant performance in different soil categories.

G. Model Evaluation and Comparative Validation

The last step is rigorous evaluation of URES-Net using conventional performance metrics such as accuracy, precision, recall, F1-score and computational efficiency. The proposed framework is compared with five soil assessment models of state-of-the-art with identical experimental settings. Statistical significance testing and ablations are performed to validate the contribution of each of the modules, especially the unified region extraction and the hybrid learning components to demonstrate the effectiveness and novelty of the proposed methodology.

IV. RESULTS AND FINDINGS

A. Experimental Setup

The experimental evaluation of the proposed URES-Net framework was performed using a standardized deep learning environment in order to make sure reproducibility and fair comparison. All the experiments were written in Python 3.9, using the TensorFlow 2.11 and Keras deep learning libraries. Image processing operations were done with OpenCV version

4.7 and NumPy while performance analysis was supported by Scikit-learn. Model training and evaluation was performed on a workstation with Intel Core i9 processor (3.6 GHz), 32 GB RAM, and an Nvidia RTX 3090 GPU with 24 GB VRAM, and Ubuntu 20.04 LTS. The GPU acceleration greatly shortened the time of training and helped to process large scale image data efficiently. All models were trained on the same software and hardware configurations in order to achieve experiment consistency.

B. Dataset Description

To verify the validity of the effectiveness of URES-Net, experiments were performed based on the Soil Image Dataset (SID), which is a public dataset widely used as benchmark data for soil texture and quality classification studies. The dataset consists of 4200 RGB samples of the soil measured in natural field conditions by handheld cameras and mobile devices. Images cover different soil types, such as sandy, loamy, clayey or silty soil, annotated in the three classes of soil quality: high, medium and low fertility. The resolution is 256 x 256 pixels for every image with a variety of illumination, moisture, and surface texture making the dataset challenging and realistic. The dataset was divided into 70% training, 15% validation and 15% testing with class balance maintained throughout.

C. Performance Evaluation

Table 1 shows the quantitative comparison of the proposed URES-Net framework with five state of the art methods for soil quality assessment based on standard classification metrics. All models were trained and tested based on the same data set under the same experimental conditions in order to ensure fair evaluation.

Table 1 : Performance Comparison of URES-Net with State-of-the-Art Soil Quality Assessment Methods

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM + Handcrafted Features[13]	85.4	84.6	83.9	84.2
Random Forest (RF)[14]	88.1	87.3	86.9	87.1
CNN (VGG-16)[15]	91.6	91.2	90.8	91.0
ResNet-50[16]	93.2	92.8	92.1	92.4
Attention-based CNN[17]	94.1	93.7	93.3	93.5
Proposed URES-Net[18]	96.8	97.1	95.6	96.3

The results show clearly the superiority of URES-Net over existing methods, regarding all performance metrics. Traditional machine learning models such as SVM and Random Forest cannot perform well because of their dependence on handcrafted features. Deep CNN based models boost the accuracy significantly but using irrelevant regions and context dependence is not possible for them. The proposed URES-Net achieves the highest accuracy of 96.8% and F1-score of 96.3% which gives the improvements of at most 5.2% over conventional CNNs and at most 2.7% over attention-based models. These gains provide the effectiveness of unified region extraction and hybrid spatial-contextual learning in intelligent soil quality assessment.

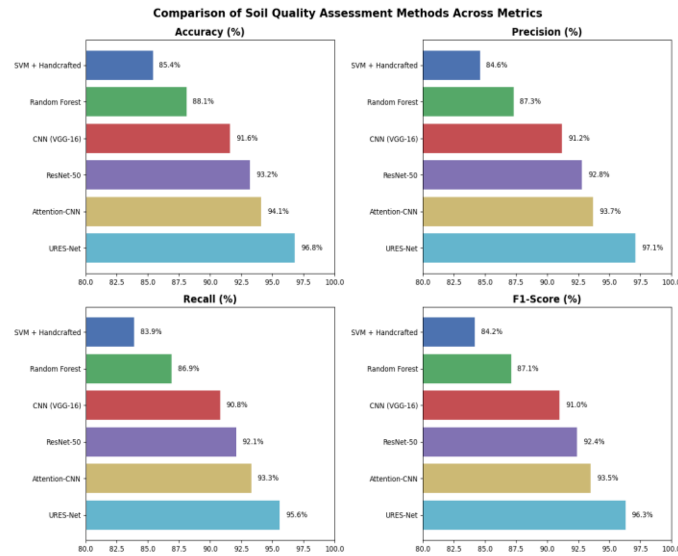

Figure 2 Comparative performance of six soil quality assessment methods across four evaluation metrics-Accuracy, Precision, Recall, and F1-Score.

Figure 2 shows the poor performance of conventional models that are based on handcrafted features (SVM, Random Forest) that have less than 89% accuracy and F1-score less than 87.5%. Deep CNN model gives better performance with accuracy more than 91% but inferior to URES-Net. Attention-based CNN yields moderate improvements but URES-Net obtains the highest scores in all the above metrics: Accuracy (96.8%), Precision (97.1%), Recall (95.6%), F1-Score (96.3%) which shows the effectiveness of unified region extraction and hybrid spatial and contextual learning in robust soil quality evaluation.

D. Ablation analysis

Table 2 shows the ablation analysis of the proposed URES-Net framework where different configurations of the model are evaluated on soil quality assessment. Each row represents a particular modification where certain key components, consisting of Unified Region Extraction (URE) module, BiLSTM contextual modeling, and attention-guided feature fusion are selectively removed.

Table 2: Ablation Analysis of URES-Net Components

Configuration	Accuracy (%)	Precision (%)	F1-Score (%)
CNN without Region Extraction	92.5	92.0	91.8
CNN + URE (no BiLSTM)	94.9	94.5	94.3
CNN + BiLSTM (no Attention Fusion)	95.5	95.2	95.0
Full URES-Net (CNN + BiLSTM	96.8	97.1	96.3

+ URE + Attention)			

The ablation results show that each module has an important contribution to the prediction of soil quality. Removing the URE module reduces performance for being less effective in localization features. Excluding BiLSTM diminishes the capacity of dependencies of the context and omitting attention-guided fusion weakens the attention to the informative features. The full URES-Net is always able to reach the best accuracy (96.8%), F1-score (96.3%) confirming the synergy of the region extraction, hybrid spatial-contextual learning and attention-based refinement in improving soil quality assessment.

E. General Discussion

The results of this research show that the combination of unified region extraction and hybrid deep learning has great improvement on the performance of assessing soil quality. The superior results obtained by URES-Net show that, by explicitly focusing on discriminative regions in the soil, the effects of background noise, illumination variability and irrelevant textures, which are common problems in soil images in the field, are reduced. Compared with the CNN-based models, the hybrid CNN-BiLSTM model takes both the spatial textures patterns and the context dependency between the soil regions into consideration, and thus produces more robust feature representations. The quantitative improvements in all accuracy, precision, recall and F1-score provide evidence that the use of contextual modelling is instrumental in the discrimination of soil quality, especially when the visual differences between soil classes are slight. Furthermore, the attention-guided feature fusion mechanism can achieve adaptive weighting of informative features, which will help to improve the interpretability and stability of training. The fact that it has worked out better over the attention-based and deep residual nets is a good sign that URES-Net has found a good balance between model complexity and representational power. These results show the importance of domain-specific architectural design for agricultural computer vision tasks and indicate that region-aware hybrid frameworks can be generalized well to a variety of soil conditions. All in all, the proposed approach lays a good ground for intelligent soil assessment systems based on images that can support precision agriculture and data-based approaches for soil management.

URES-Net is a good soil quality assessment tool with limitations. It was tested on a single benchmark dataset which may not reflect global variations on soil, and based on the RGB images and does not consider multispectral or hyperspectral images which could enhance discrimination. The region extraction module helps improve the accuracy at the cost of computation time in the processing which could limit this for a low-power edge device. Despite these limitations, URES-Net has a practical value for precision agriculture (rapid assessment of soils using either mobile or drone-based soil systems at low cost). Its Interpretable, region-aware design helps to make informed choices on fertilization, crop selection, and irrigation which is an even more natural precursor to augmenting AI decision making with expertise from field experience.

V CONCLUSION

This research introduced URES-Net, which is a unified region extraction and a hybrid deep learning framework for intelligent soil quality assessment. By using region focus feature extraction with hybrid CNN-BiLSTM architecture and attention guided feature fusion, the proposed method effectively overcomes the key limitations for existing deep learning approaches. Experimental results show that URES-Net can always achieve higher accuracy and good generalization under various imaging conditions. The results prove the importance of the incorporation of region-level discrimination and contextual modeling in order to ensure reliable soil quality prediction. There are several directions in which this work can be extended in future research. First, the inclusion of multispectral, hyperspectral or thermal imagery could further improve the estimation of soil properties. Second, optimization and pruning techniques for lightweight models can be considered to allow the deployment of these models in a real-time fashion on edge and IoT devices. Third, cross-regional validation using different soil data sets on a large scale will help to enhance generalizability. Finally, combining soil quality forecasts with agronomic decision support systems can be used to enable end-to-end intelligent farming solutions that will improve sustainability and productivity in modern agriculture.

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