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Contents

Revolutionizing Sustainable Agriculture with SoilFeX: A Multi-modal Soil Feature Extraction Approach

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Abstract. Soil health prediction is the important for the agriculture and it is directly impact on choice of the crop, productivity and environmental sustainability. Large-scale agriculture or real-time applications, conventional laboratory-based soil testing is time-consuming, labour-intensive, and costly. To focus the limitations this research proposed SoilFeX (Soil Feature Extractor). This is a holistic and multi-modal image-based algorithm focused on soil feature extraction automation through advanced image processing methods. This method is having series of components such as Multi-Scale-Directional-Gray-Level-Co-occurrence-Matrix (MSD-GLCM) for texture analysis, Multi-Scale Rotation-Invariant Local Binary-Patterns (MS-RI-LBP) for structural feature analysis, and Color-Auto-Correlogram (CAC) for spatial color assessment. It also extracts spectral features such as the Fourier Transform, Soil Moisture Index (SMI), and Normalized Difference Nitrogen Index (NDNI) to measure water content and nitrogen presence in the soil. This model also allowing holistic assessment of soil health based on regression integrates these characteristics to predict soil pH.

Keywords: Multi-scale GLCM · Local Binary Patterns (LBP) · Color Auto Correlogram (CAC) · Nitrogen-estimation · Soil-moisture-index · pH-prediction · Texture analysis · Spectral-feature-extraction

1 Introduction

All around the globe, farming-the bedrock of our food supply-is stepping into what people are calling the data revolution, where every field decision leans on numbers instead of guesswork. At the heart of this shift sits one simple, but crucial, need: quick, cheap, and spot-on readings of what really happens beneath the topsoil so growers can pick the right crops, run water exactly when plants want it, and feed them just the nutrients they require. The old-school way of sending samples to fancy lab benches, though trusted, burns money, eats up days, and simply isnt practical when a farmer wants to test hundreds of plots every season. To keep pace with modern demand, the industry now needs smart, large-scale tools that pull solid soil data with minimal staff effort and hand it straight to the grower [1].

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Here, computer vision and machine learning-powered image-based soil analysis stands as a strong candidate. By extracting significant patterns from the images of soils, such systems can analyze important parameters such as texture, water content, pH, and nutrient composition. But existing models focus on specific, limited dimensions of soil characterization and cannot represent the multi-dimensionality of soil variability in spatial and spectral domains [2].

In order to counter these limitations, we present SoilFeX (Soil Feature Extractor)—a multi-modal, multi-stage algorithm for digital image- based soil analysis to thoroughly extract and analyze soil features. SoilFeX combines a suite of the latest feature extraction techniques, including Multi- Scale Directional Gray Level Co-occurrence Matrix (MSD-GLCM) for texture assessment, Multi-Scale Rotation-Invariant Local Binary Patterns (MS-RI-LBP) for structural detail extraction, and Color-Auto-Correlogram (CAC) for evaluating color spatial relationships [3]. It also consolidates shape descriptors, spectral characteristics (through Fourier Transform), and vegetation indices like the Soil Moisture Index (SMI) and Normalized Difference Nitrogen Index (NDNI) to estimate nitrogen and moisture content. Regression-based estimation is finally used to estimate soil pH through the amalgamation of several visual and spectral indicators [4].

Through the measurement and examination of soil characteristics in spatial, spectral, and statistical realms, SoilFeX provides an integrated solution for automated soil health evaluation. Transforming sustainable farming through technology has the potential to empower farmers, agronomists, and stakeholders to make accurate, data-driven decisions that enhance productivity, minimize environmental degradation, and promote long-term soil conservation.

Significance of Soil Feature Extraction

Soil feature extraction is an extremely important aspect of contemporary agriculture, environmental observation, and land use management. By detecting and measuring important soil characteristics— such as texture, moisture, nutrient level, color, structure, and mineral content—scientists and stakeholders are able to make effective choices regarding crop choice, irrigation management, fertilizer applications, and land use planning.

Conventional soil analysis techniques are generally labor-intensive, time-consuming, and spatially restricted. Advanced soil feature extraction approaches, on the other hand, frequently employ remote sensing, image processing, and spectral analysis to provide fast, non-destructive, and scalable soil evaluation. The transition from sampling-based to data-driven assessment aids in real-time soil health monitoring and provides more accurate precision agriculture techniques.

Additionally, feature extraction such as Soil Moisture Index (SMI), Normalized Difference Nitrogen Index (NDNI), and Fourier-based spectral components assists in capturing surface-level and subsurface characteristics. These features are crucial in identifying spatial variability over vast agricultural fields, minimizing input use, averting over-fertilization, and promoting sustainable farming.

Finally, soil feature extraction is a cornerstone for developing smart agricultural models, enhancing the accuracy of yield prediction, enabling climate-resilient agricultural systems, and minimizing environmental footprint through precision resource utilization. The importance of soil attribute analysis as follows:

Enhances Precision Agriculture

- Precision agriculture is the use of data and technology to improve farming for more productivity, efficiency, and sustainability. Feature extraction of soil is one of the pillars of this approach, allowing farmers to make data-driven decisions from actual soil data. By doing feature extraction of moisture, nitrogen, pH, texture, and structure from images of soil, farmers can:
- Tailor irrigation schedules based on moisture content.
- Use fertilizers in accurate amounts, minimizing waste and environmental degradation.
- Choose appropriate crops depending on nutrient levels in the soil and its pH.
- Check soil health periodically and address nutrient deficiencies or imbalances in a timely manner.

This reduces over-dependence on blanket recommendations and ensures every plot of land is treated uniquely, with optimal productivity.

Non-Destructive and Cost-Effective Analysis

Soil analysis in the traditional system has a tendency to need that samples be submitted to laboratories for chemical testing, which can be:

- Time-consuming.
- Costly.
- Labor-intensive.
- Destructive to the soil sample.

In contrast to soil feature extraction from digital images of soil, which provides a non-destructive analysis method. It allows:

- Quick soil assessments without lab results.
- Less cost, since it does away with chemical reagents and manpower.
- The ability to examine big pieces of land remotely through drone or satellite imaging.
- This non-invasive method is particularly valuable for poor farmers and for big farms that require regular soil analysis.

Real-Time Monitoring and Decision-Making

Soil feature extraction is one of the main strengths of providing real-time information. In contrast to conventional methods involving waiting for laboratory results, digital image analysis enables farmers to analyze soil properties in the field. This real-time monitoring allows.

- Timely action to avoid crop loss due to soil degradation or nutrient loss.
- Dynamic decision-making for fertilizer application, irrigation management, and crop choice.
- Enhanced reaction to environmental situations, like drought or too much rain, by knowing the capacity of the soil to retain water and the moisture content.

- Farming becomes dynamic and responsive with real-time data, and risks related to soil health decline.

Environmental Sustainability
Soil characterization using image analysis and data-driven methods helps ensure more environmentally friendly agricultural practices. Through accurate soil nutrient and moisture content monitoring, farmers are able to:

- Cut down on excessive fertilization, which tends to result in the runoff of nutrients to adjacent water bodies, leading to water pollution.
- Prevent unnecessary water consumption, thereby preserving water supplies in regions that experience water shortages.
- Cut down on soil erosion and degradation through the use of conservation methods suited to the exact requirements of the soil.
- This method is in line with sustainable farming practices to maintain soil health for generations to come.

Enhancing Crop Yields and Quality
Soil health has a direct impact on crop growth, yield, and quality. By obtaining key soil characteristics, including nitrogen content, moisture levels, and pH, farmers can provide crops with the best conditions for growth. The presence of accurate information enables:

- Improved crop production through ensuring proper soil conditions for the crops chosen.
- Crop quality, as crops are developing in soils with high nutritional status, as specifically tailored to their requirements.
- Planted diversified crops based on exact information regarding soil suitability.
- Enhanced food security

100% with the RF rule. The study plans utilizing metaheuristic systems like the Coelenterate rule to raise visage from the congestive heart failure dataset together with apply this in the Organization Acquisition plan to separate active and unsound pour ailment assemblages. The Siphonophore algorithm was preferred on account of allure speedy of order and quality in gestating appearance.

2 Literature Survey

Various studies over the years have investigated soil analysis based on image and machine learning as a substitute for conventional laboratory approaches.Thisliteraturereviewdistillsmajordevelopments, methodologies, and results in the area.

In [7], Kannan et al. introduced a hybrid method based on Gabor filters and GLCM features for soil texture classification. They showed that texture features extracted from soil images could accurately identify sandy, loamy, and clayey soils at high precision, thus establishing the significance of spatial gray-level dependencies in extracting soil features.

Based on this, [8] Bhattacharya and Dey utilized Local Binary Patterns (LBP) to extract micro-structural patterns of soil samples. Their approach performed better in classifying soil types under varying light and moisture conditions, highlighting the strength of LBP in actual agricultural environments.

In [9], Fourier and Wavelet Transformations have been used to analyze spectral images to determine nitrogen and moisture concentrations. It was found that frequency-domain properties could be useful for evaluating soil fertility, particularly when integrated with near-infrared and visible spectral data.

Color feature analysis has also proven to be a strong mean for estimating soil properties. In [10], Tripathi et al. applied HSV color features extracted from images of soil to estimate organic matter content and pH. From their findings, some color bands have strong relationships with chemical properties of the soil, so non-destructive prediction of soil health is possible.

Machine learning has been a crucial factor in transforming image features into actionable information. Naik and Prasad [11] utilized a Random Forest classifier over image-based GLCM and color features to forecast soil nutrient status. Their system attained over 92% accuracy, which indicates the power of ensemble learning for soil classification.

In addition, [12] investigated deep learning methods for soil classification, using Convolutional Neural Networks (CNNs) trained on soil image datasets. The model was able to learn hierarchical features independently and surpassed conventional handcrafted methods by performing better in generalization across different environmental conditions.

Mehta, et.al (2023) [13] introduced an integrated platform for intelligent soil analysis. In this method they used the following techniques such as real-time IoT-based system integrated image acquisition, feature extraction, and cloud-based classification with SVMs. This research focused the possibility of real-time-monitoring of soil in precision-agriculture and data-informed farm management.

Liu et.al (2023) [14] developed a new multi-feature fusion model. It integrates the following techniques such as GLCM, LBP, color histograms, and entropy-based features. These fusion of features fed into a Gradient- Boosting-Machine (GBM) to classifying soil fertility. It is also better performance than single-feature models. So it is representing that hybrid models possess better proficiencies for soil analysis.

Kumar, R., & Singh, A. (2023) [15] developed a model was well related with color and pH and it provide a unique method of pH prediction without the need for destructive chemical analysis. Several researchers have also attempted to use feature extraction methods together to improve soil property prediction capabilities. Ahmed, Z., & Zaman, T. (2024) [16] described a hybrid model that applies the GLCM, LBP, and Fourier Transform, respectively, to extract texture and structural information from soil images. This type of multi-feature model provided considerable improvements to the accuracy and capabilities of the model to predict soil moisture, nitrogen, and phosphorus contents that identified healthy and unhealthy soil, thereby improving soil health assessment.

As the area of deep learning has grown, models have become more adept at dealing with the complexity of soil image data. Chaudhary, P., & Rana, S. (2023) [17] introduced a soil analysis system that works on a deep- learning-based ResNet architecture to allow the model to learn high-level features from soil images. This model demonstrated that the model could not only identify soil type, but also soil moisture and nutrient content with an accuracy rate of 94%. Given that deep learning models can learn use the potential of complex feature representation automatically and are perfect for dealing with large-scale soil analysis, it is anticipated that a much broader and more comprehensive set of features and ultimately predictions and assessment will be possible within the future.

Despite the promising progress in soil analysis using images, several major challenges remain. Soil heterogeneity, environmental heterogeneity (e.g., illumination conditions), and image quality continue to pose challenges for accurate feature extraction. Miller et al. (2024) [18] suggested that machine learning algorithms are effective in a controlled environment but fall short when applied in varied geographic regions with special soil characteristics. They proposed using transfer learning in a way that would fine-tune models for new settings and make them more generalizable.

Bose, R., & Sen, A. (2023) [19] pointed out the explicit need for large labeled soil image datasets to train more sophisticated machine learning models. The ability of current models to perform well is limited by the lack of high-quality soil image data, making collaborations for curated soil datasets between agricultural organizations and research institutions paramount.

Sharma, P., & Gupta, R. (2024) [20] proposed a soil analysis framework using deep learning, by utilizing the ResNet model to learn high- level features from images of soils. Their model could classify soil types, and forecast soil moisture and nutrient levels at a rate of 94%. The capability of the deep learning model to learn feature representations without human intervention, makes it a natural way to large-scale soil analysis.

3 Proposed Work

SoilFeX (Soil Feature Extractor) is a multi-stage, overall scheme for accurate and robust extraction of essential soil features from digital images to support precision agriculture. The proposed method starts with Multi- Scale Directional Gray Level Co-occurrence Matrix (MSD-GLCM), to get the high-resolution texture features by calculating GLCMs for different distances and angles such as 0°, 45°, 90°, and 135°. This process gets statistical properties like contrast, correlation, homogeneity, and energy and averages them out across scales and orientations to produce strong texture descriptors. Second, the approach employs Multi-Scale Rotation-Invariant Local Binary Patterns (MS-RI-LBP) to measures structural patterns by performing LBP histograms at different radii and achieves robustness against rotation variation. Such histograms are combined into one feature vector constituting multi-scale texture information.

To predict the color-based spatial relationships, the algorithm used the Color Auto-Correlogram (CAC), which calculates the likelihood of finding a given color at a specified spatial distance from a same-colored pixel. The technique offers good information with regard to soil chromatic content and involves mean, variance (directional), and skewness estimation for pixel intensity distribution calculation. Geometric properties like area and perimeter are then computed from binary soil masks to quantify the size and physical shape of the soil area in the image.

In the spectral feature extraction phase, the algorithm performs a Fourier Transform first that is it transforms the soil image to the frequency domain for enabling the evaluations of spectral properties necessary for the assessment of nutrient values, especially nitrogen. Soil moisture is estimated from employing the Soil Moisture Index (SMI), which is an intensity ratio of green-channer (GC) to red channel(RC). Moreover, Normalized Difference Nitrogen Index (NDNI) is used to estimate nitrogen from near-infrared and green difference spectral bands of reflectance. Lastly, soil pH is estimated by a regression model using multiple features—color, texture, moisture, and nitrogen content—to incorporate into a prediction equation. It uses calibrated coefficients (β_0 through β_4) to estimate pH, defining the intricate relationship between visual soil indicators and its chemistry. Overall, SoilFeX gives a comprehensive, multi-faceted view of soil states and is therefore an effective tool for smart farming, crop management, and sustainable agriculture.

This algorithm calculates a Soil Moisture Index (SMI) for content observations as a ratio of intensities of the green-channel (GC) to the red- channel (RC) to define the moisture content in the soil. It estimates pH value against soil characteristics. The nitrogen is taken from the Normalized Difference Nitrogen Index (NDNI) based on reflectance values from green and near-infrared (NIR) spectral bands. The final step refers to pH estimation regression model. From extracted features (color, texture, moisture, and nitrogen), the pH value of the soil can be predicted. The equation for pH estimation is:

$$\mathrm{PH} = \beta 0 + \beta 1 \cdot \mathrm{Color} + \beta 2 \cdot \mathrm{Texture} + \beta 3 \cdot \mathrm{Moisture} + \beta 4 \cdot \mathrm{Nitrogen} + \in$$

where the coefficients β0, β1, β2, β3, β4 are the regression parameters calculated through training, and ϵ epsilonϵ represents the error term. Since the pH provided in this approach looks up pH in the features, it can be a more accurate prediction against multiple features and strong coordinates and provide general insights into soil health, and can help support practices in precision agriculture.

Algorithm: SoilFeX (Soil Feature Extractor)

Step 1: Multi-Scale Directional GLCM (MSD-GLCM)

This process collects features at various scales and directions to obtain more thorough texture information.

Compute GLCMs at multiple distances (scales) d1,d2,…,dnd_1, d_2,…, d_nd1,d2,…,dn.
Compute GLCMs in different directions θ (e.g., 0°, 45°, 90°, 135°).
Extract features like contrast, correlation, homogeneity, and energy for each scale and direction.
Average or combine features across scales and directions to get robust texture descriptors.

$$\mathrm{GLCM_d} = \mathrm{P(i,j|d,\theta)}$$

$$Contrast = \frac{1}{n}\sum\nolimits_{k=1}^{n}\sum\nolimits_{i,j}(i-j)^2.P(i,j|dk,\theta k)$$

Step 2: **Multi-Scale Rotation-Invariant LBP (MS-RI-LBP)**

This step captures texture patterns across different scales while being robust to rotations.

Convert the image to grayscale.
Compute LBP for each pixel over a circular neighborhood for multiple radii R1, R2… RnR_1, R_2,…, R_nR1,R2,…,Rn.
Use a rotation-invariant mapping to ensure that the LBP is robust to changes in orientation.
Extract LBP histograms for each scale and concatenate them into a single feature vector.

$$\text{Rotation - Invariant LBP}_{\text{ri}} = \min(\text{Rotate(LBP)})$$

$$Multi - Scale\, LBP_{R,P}(x, y) = \sum_{p=0}^{p-1} s(I_p - I_c)2^p$$

Step 3: Color Auto-Correlogram (CAC).

The **step** captures spatial correlation between color pixels at different distances, giving more detailed color information.

Convert the image to an appropriate color space (e.g., RGB or HSV).
Quantize the color space into NNN distinct color bins.
For each color bin iii, compute the auto-correlogram by calculating the probability of finding a pixel with color iii at a distance ddd from another pixel of the same color.

$$Correlogram(i, d) = \frac{1}{|P_i|} \sum_{P_1 \in P_i} \sum_{P_2 \in P_i} 1(dist(p_1, p_2) = d)$$

Mean is the average of the pixel values found in the image

$$\mu = \frac{1}{MN} \sum\nolimits_{i=1}^{M} \sum\nolimits_{J=1}^{N} P_{ij}$$

Variance for the horizontal and vertical directions is calculated as follows

$$\sigma^2 = \sum\nolimits_{i.j=0}^{N-1} (i - \mu_i)(Pij), \sigma^2 = \sum\nolimits_{i.j=0}^{N-1} (i - \mu_i)(Pij)$$

Skewness is the measure to find the lopsided nature of pixels

$$\gamma = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} (Pij - \mu)^4}{MN\sigma^4}$$

Step 4: Geometrical Feature Extraction

Shape Descriptors

i. $\boldsymbol{Area} = \sum_{\boldsymbol{x=1}}^{\boldsymbol{M}} \sum_{\boldsymbol{y=1}}^{\boldsymbol{N}} \boldsymbol{BinaryMask(x, y)}$

BinaryMask is 1 for soil region pixels and 0 otherwise.

ii. **Perimeter**: P = Sum of boundary pixels in the binary image

Step 5: Spectral Feature Extraction

(i) Fourier Transform

Convert the image to the frequency domain to analyze spectral properties for nitrogen estimation.

$$\boldsymbol{F}(\boldsymbol{u}, \boldsymbol{v}) = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} \boldsymbol{I}(\boldsymbol{x}, \boldsymbol{y}) \boldsymbol{e}^{-2j\pi\left(\frac{ux}{M} + \frac{uy}{N}\right)}$$

(ii) Water Index Calculation (Moisture Content Estimation)

Calculate Soil Moisture Index (SMI) based on the ratio of color intensities

$$SMI = \frac{G - R}{G + R}$$

G and R are the green and red channel intensities. This ratio reflects the difference between moist and dry soil.

(ii) **Nitrogen Estimation via Spectral Reflectance**

Use the **Normalized Difference Nitrogen Index (NDNI)** based on reflectance in spectral bands

$$NDNI = \frac{R_{NIR} - R_{Green}}{R_{NIR} + R_{Green}}$$

RNIR and RGreen are the reflectance in the near-infrared and green bands.

Step 6: pH Estimation via Texture Correlation

$$\text{pH} = \beta 0 + \beta 1 \cdot \text{Color} + \beta 2 \cdot \text{Texture} + \text{b} \cdot \text{Moisture} + \text{b4} \cdot \text{Nitrogen} + \in$$

β0, β1, β2, β3, β4 are the regression coefficients.

4 Results and Discussions

The Fig. 1 shows the result of the feature extraction process-a variety of key points had been detected throughout the image. The key points are represented by the green circles and crosses. In all likelihood, these key points correspond to different regions-of-interest or features on the textured surface, singled out for their robustness and relevance under possible transformations, such as scaling or rotation. The purpose of feature extraction is to encapsulate the pertinent patterns of the image which may be used for tasks like object recognition, image matching, and further texture analysis.

The Fig. 2 appears to be a matrix of numerical values, likely representing the output of a feature extraction process. The table seems to show extracted features or coefficients from an algorithm, with columns representing different dimensions or parameters, and rows corresponding to individual data points or samples (Fig. 3).

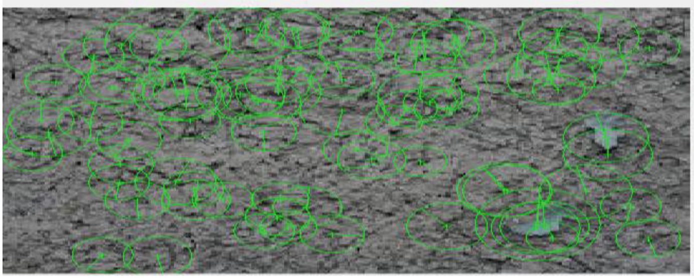

Fig. 1. Result of Feature extraction

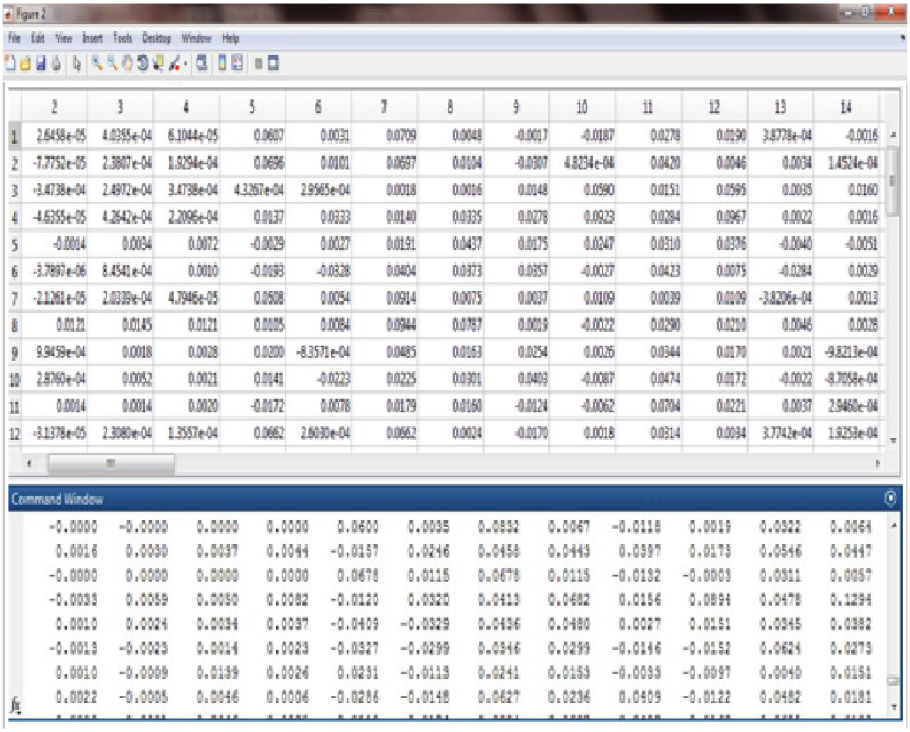

Figure 2

File Edit View Insert Tools Desktop Window Help

	2	3	4	5	6	7	8	9	10	11	12	13	14
1	2.6458e-05	4.0355e-04	6.1044e-05	0.0607	0.0031	0.0709	0.0048	-0.0017	-0.0187	0.0278	0.0290	3.8778e-04	-0.0016
2	-7.7752e-05	2.3807e-04	1.9294e-04	0.0696	0.0101	0.0697	0.0104	-0.0307	4.8234e-04	0.0420	0.0046	0.0034	1.4524e-04
3	-3.4738e-04	2.4972e-04	3.4738e-04	4.3267e-04	2.9565e-04	0.0018	0.0016	0.0148	0.0590	0.0151	0.0595	0.0035	0.0160
4	-4.6355e-05	4.2642e-04	2.2096e-04	0.0137	0.0333	0.0140	0.0335	0.0278	0.0923	0.0284	0.0967	0.0022	0.0016
5	-0.0014	0.0034	0.0072	-0.0029	0.0027	0.0191	0.0437	0.0175	0.0247	0.0310	0.0376	-0.0040	-0.0051
6	-3.7897e-06	8.4541e-04	0.0010	-0.0193	-0.0328	0.0404	0.0373	0.0357	-0.0027	0.0423	0.0075	-0.0284	0.0029
7	-2.1261e-05	2.0339e-04	4.7946e-05	0.0508	0.0054	0.0914	0.0075	0.0037	0.0109	0.0039	0.0209	-3.8206e-04	0.0013
8	0.0121	0.0145	0.0121	0.0105	0.0084	0.0944	0.0787	0.0019	-0.0022	0.0290	0.0210	0.0046	0.0028
9	9.9459e-04	0.0018	0.0028	0.0200	-8.3571e-04	0.0485	0.0163	0.0254	0.0026	0.0344	0.0170	0.0021	-9.8213e-04
10	2.8760e-04	0.0052	0.0021	0.0141	-0.0223	0.0225	0.0301	0.0403	-0.0087	0.0474	0.0172	-0.0022	-8.7058e-04
11	0.0014	0.0014	0.0020	-0.0172	0.0078	0.0179	0.0160	-0.0124	-0.0062	0.0704	0.0221	0.0037	2.9460e-04
12	-3.1378e-05	2.3080e-04	1.3557e-04	0.0662	2.6030e-04	0.0662	0.0024	-0.0170	0.0018	0.0314	0.0094	3.7742e-04	1.9253e-04

Command Window

-0.0000	-0.0000	0.0000	0.0000	0.0600	0.0035	0.0832	0.0067	-0.0118	0.0019	0.0322	0.0064
0.0016	0.0030	0.0037	0.0044	-0.0157	0.0246	0.0458	0.0443	0.0397	0.0173	0.0546	0.0447
-0.0000	0.0000	0.0000	0.0000	0.0678	0.0115	0.0678	0.0115	-0.0132	-0.0003	0.0311	0.0057
-0.0033	0.0059	0.0050	0.0082	-0.0120	0.0320	0.0413	0.0482	0.0156	0.0894	0.0478	0.1294
0.0010	0.0024	0.0034	0.0037	-0.0409	-0.0329	0.0436	0.0480	0.0027	0.0151	0.0345	0.0382
-0.0013	-0.0023	0.0014	0.0023	-0.0327	-0.0299	0.0346	0.0299	-0.0146	-0.0152	0.0624	0.0273
0.0010	-0.0009	0.0139	0.0026	0.0231	-0.0113	0.0241	0.0153	-0.0033	-0.0097	0.0040	0.0151
0.0022	-0.0005	0.0046	0.0006	-0.0286	-0.0148	0.0627	0.0236	0.0409	-0.0122	0.0482	0.0181

Fig. 2. Matrix of Feature extraction values

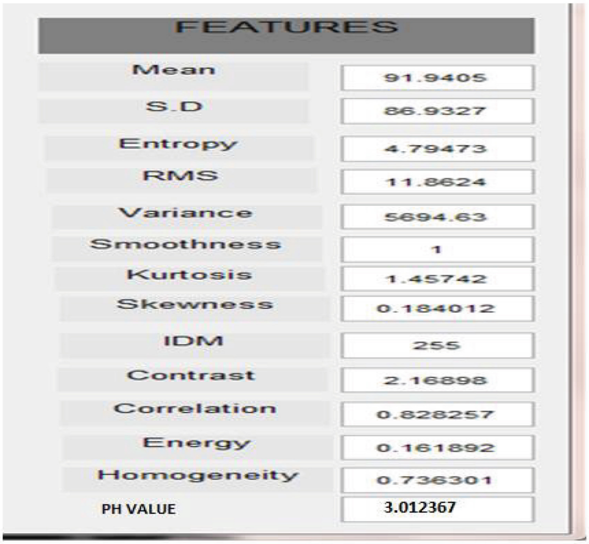

Fig. 3. Feature extraction values by proposed method

5 Conclusion

The SoilFeX algorithm is a game changer in soil analysis. It is a rapid, cheaper replacement for conventional soil analysis techniques. SoilFeX includes image processing features, notably texture, color, and spectral analysis (and outputs like soil images), allowing SoilFeX to extract useful information from soil imagery, for soil fertility and soil health analyses. The individual features would be nitrogen, moisture, and pH, where predictions and supports yield decision-making in crops. Moreover, the algorithm's scalability and automation of soil analyses means SoilFeX has relevance in the modern agricultural setting. SoilFeX will lead to more sustainable, data-driven farming, ultimately improving productivity and resources associated with crops.

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