ICPA
17th INTERNATIONAL CONFERENCE ON PRECISION AGRICULTURE
ConBAP 2026
CONGRESSO BRASILEIRO DE AGRICULTURA DE PRECISÃO E DIGITAL
13-16 July 2026 | Porto Alegre, Brazil
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Soil Texture Classification by Image: Deep Feature Learning vs. Handcrafted Methods for Precision Agriculture

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A paper from the Proceedings of the

17th International Conference on Precision Agriculture and 11th Brazilian Congress on Precision and Digital Agriculture

13-16 July 2026

Porto Alegre, Brazil

Abstract. Soil texture is a fundamental physical property that directly influences water retention, nutrient availability, and crop productivity, making its accurate classification essential for precision agriculture and site-specific management. Conventional laboratory methods, such as the pipette and hydrometer techniques, are accurate but time-consuming, labour-intensive, and dependent on specialised infrastructure, which limits the dense spatial sampling often required to characterise within-field variability. Deep feature learning was compared against three classical handcrafted texture descriptors for the automatic classification of soil texture from close-range microscope images acquired in a controlled environment, rather than from aerial, orbital, or smartphone imagery. A dataset of 1,388 close-range images was acquired with a MOYSUWE MDM201 Pro digital microscope (16 MP Sony CMOS IMX sensor; 5376 × 3024 pixels) under controlled indoor conditions, with each soil sample placed in a standard Petri dish; a one-to-one correspondence between images and physical samples was maintained to prevent data leakage between cross-validation folds. Four feature extraction strategies were evaluated: deep features from a pre-trained SqueezeNet convolutional neural network, the Fast Fourier Transform (FFT), Gabor filter banks, and Local Binary Patterns (LBP). For each feature set, five classifiers were assessed: k-Nearest Neighbours, Support Vector Machine, Random Forest, Logistic Regression, and an Artificial Neural Network (ANN); a stratified 10-fold cross-validation protocol was applied across four textural classes (Sandy, Medium, Clayey, and Very Clayey). Samples and reference labels were supplied by a national-scale soil analysis laboratory whose results are externally validated through an established proficiency-testing programme. SqueezeNet features combined with an ANN achieved 78.0% accuracy, outperforming the best handcrafted combinations by 11.6 to 23.7 percentage points; the strongest handcrafted results were LBP + kNN (66.4%), Gabor + Random Forest (62.8%), and FFT + Random Forest (54.3%). Among the four textural classes, the Medium class was the most difficult to classify with the best pipeline, reflecting its position as a textural transition zone between the coarser Sandy and finer Clayey classes, whereas the Sandy class was among those most accurately classified by the deep features. These findings indicate that compact CNN-based transfer learning (approximately 0.5 MB model size) provides a substantial accuracy advantage over handcrafted descriptors while remaining lightweight enough for field-deployable systems, supporting its use as a practical foundation for image-based soil texture classification in precision agriculture workflows.

Keywords. soil texture classification; precision agriculture; convolutional neural networks; transfer learning; texture descriptors; digital microscopy

Introduction

Soil texture controls water retention, nutrient availability, and crop productivity, and its spatial knowledge underpins site-specific management in precision agriculture (Mulla 2013). Conventional granulometric analysis by the pipette and hydrometer methods is accurate but time-consuming and infrastructure-dependent (Gee and Bauder 1986), which limits the dense sampling needed to characterise within-field variability. Image-based classification offers a faster, lower-cost alternative. Two method families compete: handcrafted texture descriptors (FFT, Gabor filter banks, and LBP) and deep features learned by convolutional neural networks (CNNs) through transfer learning. The objective of this study was to determine whether deep features from a compact pre-trained SqueezeNet network classify close-range soil images more accurately than the three handcrafted descriptors, under identical classifiers and validation.

Materials and Methods

Soil samples were provided by a national-scale soil analysis laboratory, with reference textural labels (Sandy, Medium, Clayey, Very Clayey) assigned by standard granulometric analysis (Gee and Bauder 1986) and externally validated through a proficiency-testing programme. Each sample was placed in a standard 90-mm Petri dish and imaged once with a MOYSUWE MDM201 Pro digital microscope (MOYSUWE, China; 16 MP sensor; 5376 × 3024 pixels) under constant LED illumination, yielding 1,388 images with a one-to-one image-to-sample correspondence that prevented data leakage between folds. Four feature sets were extracted: deep SqueezeNet embeddings (Iandola et al. 2016) reduced by principal component analysis (PCA) to 41 components, and the FFT, Gabor (Jain and Farrokhnia 1991), and LBP (Ojala et al. 2002) descriptors. Each set was paired with five classifiers (kNN; support vector machine, SVM; Random Forest; Logistic Regression; and ANN) in Orange Data Mining (Demšar et al. 2013), giving 20 combinations evaluated by 10-fold stratified cross-validation.

Results and Discussion

Across all 20 combinations, the SqueezeNet deep features classified with the ANN achieved the highest accuracy (78.0%; area under the curve, AUC = 0.945) and outperformed every handcrafted descriptor (Table 1). Among the handcrafted methods, LBP with kNN was the strongest (66.4%), followed by Gabor with Random Forest (62.8%) and FFT with Random Forest (54.3%); the ordering matched the descriptors' sensitivity to micro-textural detail. For the best pipeline, the Medium class was the most difficult (per-class precision 62.8%), with most confusion drawn from the adjacent Sandy and Clayey classes rather than from Very Clayey, indicating a genuine textural transition zone rather than an effect of class size.

Table 1. Best-performing classifier for each feature extraction method (10-fold stratified cross-validation), ordered by classification accuracy (CA). The final column reports the difference from the best deep-feature combination, in percentage points (pp)

Method	Type	Best classifier	CA	Δ vs. deep (pp)
SqueezeNet (+ PCA)	**Deep**	**ANN**	**0.780**	**—**
LBP	Handcrafted	kNN	0.664	−11.6
Gabor filter bank	Handcrafted	Random Forest	0.628	−15.2
FFT	Handcrafted	Random Forest	0.543	−23.7

Conclusion

On 1,388 independent close-range soil images, deep features from a pre-trained SqueezeNet network classified with an ANN achieved 78.0% accuracy, exceeding the best handcrafted combination by 11.6 and the weakest by 23.7 percentage points. Given its 0.5 MB footprint, the compact transfer-learning pipeline is a practical foundation for image-based soil texture analysis in precision agriculture. Future work will examine alternative textural-class boundaries, other acquisition setups, network fine-tuning, and integration into a field-deployable workflow.

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