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SOIL CLASSIFICATION USING MOBILENET MODEL

Anongporn Salaiwarakul

Department of Computer Science and Information Technology
Faculty of Science
Naresuan University
99 Moo 9, Muang, Phitsanulok 65000, Thailand
anongporns@nu.ac.th

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Abstract. *Agriculture is a major contributor to the national economy in developing countries. Image processing has been applied in several aspects for enhancing the effectiveness of the agricultural industry, such as for monitoring plant diseases and plant yields, and to increase crop productivity by analyzing soil characteristics and soil classifications, as well as environmental factors such as area, water supply, temperature, and humidity. Any factors which are crucial for selecting appropriate crop types for a specific area to enhance crop yields and quality can be considered. This research focuses on analyzing the crucial factors in pre-harvesting processes by implementing the MobileNet deep learning model for identifying and classifying soil types. Six different soil classes were classified by applying the proposed soil classification model. The outcome of the analysis shows that the model achieved the best accuracy in identifying class "sand" with "clay" being identified with the lowest accuracy. The closeness of soil color affects the accuracy in classifying the soil class which is the challenge of this research.*
Keywords: Soil classification, Deep learning, Agriculture, MobileNet

1. **Introduction.** Traditionally, farming depends on the farmers' experience and ability to control the factors that affect crop cultivation. Some important parameters greatly affect productivity, relevant to both the harvesting processes and the pre-harvesting processes. Good information regarding these factors will enhance agricultural productivity and a paucity of good information will reduce crop yields. Hence, identifying and analyzing the parameters that impact crop yields and crop quality is crucial in farming. Smart farming utilizes various technology-enabled methods such as the IoT, the use of drones, and machine learning to accomplish better farming outcomes and crop yields. For example, machine learning techniques are employed in the prediction, identification, and classification of crop diseases, crop productivity and yield while IoT sensors have been used for monitoring soil nutrients and moisture [1].

Artificial Intelligence (AI) has been applied in smart agriculture to increasing productivity and is fast, precise, and convenient [2,3]. Deep learning and image-processing techniques have also been applied in the agricultural sector [4,5] in various ways, including monitoring fruit diseases [6,7] where the diseases were classified, and particular diseases mapped to their categories. The recognition, identification, and classification of leaf pests and leaf diseases, using deep learning techniques, have also been reported [8,9]. The identification of symptoms of nutrient deficiency shown in plant leaves has also been discussed [9-11]. The Convolutional Neural Network (CNN) and Support Vector Machine (SVM) model for analyzing plant leaf diseases was demonstrated in [12]. These research projects demonstrate that the application of image processing and techniques is well-known and demonstrated in the harvesting stage, but little work has been done for the application of

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these technologies in the pre-harvesting stage which is equally important for productivity and crop quality.

Related parameters affecting agriculture productivity in the pre-harvest processes include soil water availability and precipitation frequency, humidity, nutrients, and soil types. An understanding of the appropriate levels of these factors, and the ability to control them optimally, can significantly improve cropping productivity and product quality. Therefore, recognizing, observing, identifying and characterizing these parameters are crucial elements in smart agriculture. The inter-relationships between these various factors and the different crop plant types are complex and difficult to comprehend and modify for the most optimal outcomes. Technology solutions are necessary to handle this complexity, enabling farmers to better and more immediately understand and account for these pre-harvest factors, thereby improving their yields and producing quality produce.

Knowledge of soil types is a crucial decision-making factor that affects crop productivity and product quality, as well as enabling plans and actions for soil improvement and plant type selection appropriate to the soil classification. Personal knowledge and experience are significant factors in understanding soil types and associated plant and crop decisions, and farmers' local knowledge potentially provides a rich resource for analysis by AI means.

Identifying nutrients in the soil and classifying soil types could apply image processing and deep learning techniques. A k-Nearest-Neighbors (kNN) model was applied to the identification and classification of the essential soil nutrients nitrogen, phosphorus, and potassium [13]. The information available in the OpenCV library has been applied to the measurement of pH levels and nutrient contents in the soil [14].

Machine learning approaches, including image processing and deep learning techniques, could be beneficially adopted to increase effectiveness and efficiency in smart farming and agriculture sectors. A comparison of image processing and deep learning techniques for soil classification was undertaken in [15]. An exploration and categorization of soil characteristics were presented in [16,17] in which machine learning and image processing techniques were applied. The SVM model was applied for soil classification in [16,17] where a soil color sensor program, running on a smartphone, for soil type classification based on soil diversity of color, was developed. In this latter case, a more detailed analysis of soil categories based on color would be required as the color of different soil categories can be very similar. The current research emphasizes color recognition in soil classification.

Following previous research into the classification of soil types in the variety of ways presented, the objectives of this proposed research were to classify six different soil types by applying the deep learning model and then implemented it on mobile devices. The model is intended as a basis for the further development of technology-enabled tools for farmers to adopt and successfully apply in smart farming practices. The deep learning model for this research is illustrated in Section 3, followed by the experimental results which are shown in Section 4. Section 5 includes the conclusion and discussion components of the paper.

2. **Background.** To increase agriculture productivity, monitoring the parameters that affect crop yield and product quality is crucial. Image processing and deep learning techniques have been widely studied for their application in image analysis for the detection, identification, and classification of factors that adversely, or beneficially, affect agricultural productivity. As a major contributor to the national GDP of most countries, and especially developing countries, advances in crop productivity and quality are significant. Knowledge of soil type, composition, and nutrient and water content is an essential element in agricultural success. Soil can be categorized under several types such as clay, silt, loam, and sand, which can be sub-categorized as clayey soil, silty soil, sandy soil and loamy soil, or sandy clay, silty clay, clayey sand and silty sand. Different categories of soil

have different soil compositions and nutrient content, making an understanding of local soil types of imperative for successful farming and the selection of crop types.

The texture of soils categorized as clay is flexible and has a high moisture-holding ability which is suitable for planting rice, for example. Sandy clay particles in clays and sandy soils have low nutrient levels and water-holding capacities. Plants that are suitable for this class of soil are chili, eggplant, papaya, and rice. Silty clay and loams have greater water holding capacity and allow better aeration and are good for plantings of vegetables such as pumpkin and peas, and even fruit trees such as mango and rambutan. Loam has fine particles and a high level of nutrients. However, loamy soils are not widespread in areas where sandy river silts are common as a result of annual flooding in modern and geological times.

Sand has larger particles than clays, silts and loams and has low nutrient value and lacks moisture-holding ability and is therefore not suitable for most crops. Loam has fine particles which maintain nutrients and allows aeration and excess water drainage, making it suitable for planting. Sandy loam has a mixture of loam and sand and retains moisture well and has good aeration while also allowing excess water drainage, thus avoiding excess water stress. Loamy soils are the most suitable for planting most crops. So, importantly, different soil types have different physical and chemical properties and have different and distinct colors and textures that can be identified by a variety of color analysis and image processing technologies that are currently available.

This brief review of the types and usage of soil shows that understanding the soil characteristic and classifying soil types are important in successful agriculture cultivation. Traditionally, the soil type and the soil improvement are differentiated using personal experience and local knowledge which might not be available to inexperienced farmers newly entered to the agriculture sector. The adoption of image processing and deep learning technique for soil classification would be easy and convenient for employing the model in smart agriculture.

The nutrient content in soil significantly affects the quality of the crop that is planted in that soil, in this case, the quality of essential oils as discussed in [13] where the image processing technique, kNN, was applied to identifying the nutrients Nitrogen, Phosphorus, and Potassium, generally labelled NPP. In that research, 693 soil images were used for training and 297 images for testing. The researchers proposed 5 classes of each nutrient: very low, low, moderate, high, and very high and then were able to show that the soil colors in soil images could be used to identify the level of soil nutrients. This is a very convenient way of identifying nutrients.

To further improve the accuracy of soil image classification, image feature selection is important. In [18], a new feature selection approach was proposed that reduced the redundant and irrelevant image features in soil classification. The proposed Oscillating Spider Monkey Optimization (OSMO) algorithm improved soil classification accuracy by 2.5%.

A study of applying a deep convolutional neural network to the classification of soil aggregate size was undertaken in [19]. That study defined six classes ranging from finest to coarsest grain soil size and analyzed the soil using Inception-v4, VGGNet16, and ResNet50 where the proximity of the textual feature among each class was indicative of the complexity in distinguishing the soil grain size classification. The accuracy achieved by these deep learning models was compared.

Several techniques for image processing were illustrated and compared in [15] which showed that CNN is a more effective technique for soil classification than other techniques such as SVM, ANN, or RNN.

The deep learning approaches are more effective when a sufficient number of images are available for training. The image classification for soil that was proposed in [20] applied machine learning, deep learning, and transfer learning using CNN, Inception ResNet V2, and VGG16 to handling the problem of inadequate data. Accuracy was low due to the small number of images used in the studied model even though the augmentation technique was applied to creating more images. For the deep learning approach to be effective a large amount of data and processing resources are required, which has made them unsuitable for employment on mobile devices.

MobileNet is a class of CNN which is a small, lightweight model requiring fewer processing resources. Notwithstanding that the accuracy of this model is low when compared to other types of deep learning models, it is suitable to be embedded in mobile applications [21]. The MobileNet model has been applied in various fields of study in classifying and recognizing images: facial recognition [22,23,29], and in the agricultural sector [24-28]. Some studies have employed MobileNet in mobile applications for identifying plant diseases [27,28], demonstrating its employment on mobile devices, and ease of use by users via a smartphone.

A review of previous studies showed that the majority applied image processing techniques in the harvesting stage while the pre-harvesting stages that utilized the deep learning technique are rarely found. Although some soil classification researches applying image processing techniques and deep learning models were studied, different deep learning models could not be applied for classification due to different regions having different soil types. Importantly, the limited resources available on mobile devices challenge the development of an accurate deep-learning model for mobile devices such as smartphones. The objective of the current research is to develop a deep-learning model that can achieve an acceptable level of accuracy on a mobile device.

3. **Research Framework.** This research proposed an image-processing technique that can identify and classify six different types of soil. The framework of this research was composed of three processes: data acquisition, the development of a deep learning model, and the development of a soil classification mobile application. Figure 1 illustrates this research framework. The data set for this research was a collection of soil images that enabled the 6 different classes of soil to be identified and analyzed. The soil images were used to train in MobileNet model and classify the soil types for further analysis.

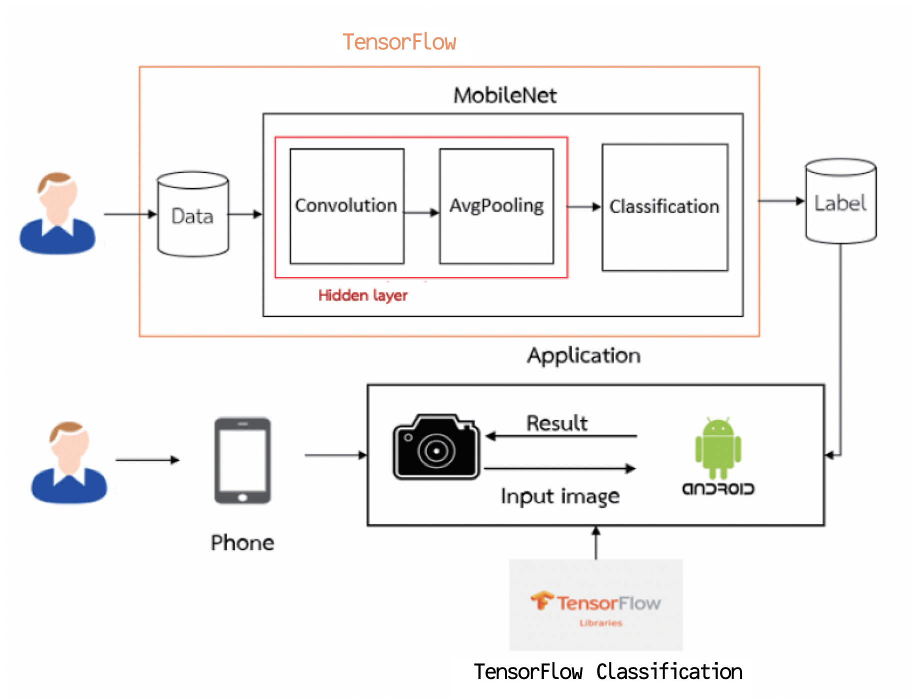

Figure 1. The research framework

Data Acquisition. The images collected for this research were taken with a smartphone. The quality of these images was sufficient to ensure the ability of users to collect such images in the field and use them in the deep learning model that we developed. The data was collected for six different soil classes: clay, silty clay, sandy clay, loam, sandy loam, and sand each of which had 100 sample images, giving 600 pictures in total for the training process. The images are both from the photos collected by the researcher personally, and from available images stored on the Internet, providing significant variations of input image quality. The sample images used for image classification are shown in Figure 2.

(a) Clay (b) Silty clay (c) Sandy clay

(d) Loam (e) Sandy loam (f) Sand

Figure 2. Sample images of soil for classification

The Soil MobileNet Model. The model that was used in this research was the MobileNet model which has been proven to be suitable for image classification applications on mobile phones. The TensorFlow library was imported for inclusion in the model development. The deep learning model which was developed in this research was specified as a mobile application with ease of use for farmers, enabling the farmer to classify soil types and assist them to identify appropriate crops suitable for the soil on their holdings. It was also intended that the model could be used as the core technology for developing mobile applications for other aspects of farming and cropping that could help farmers to improve the quality of their soil and to select the most suitable cropping plants for that soil type, thereby ensuring optimal crop yields and produce quality.

When MobileNet is applied as the classification model, convolution and average pooling techniques were applied to the images, which were further classified for model training purposes.

Soil Classification Mobile Application. The mobile application was developed to include the deep learning model to support the farmer in identifying and classifying the soil type in his area. Ease of use was a requirement which was achieved by having the application on a mobile device, particularly a smartphone, enabling the farmer to use a mobile phone in the field to take pictures of the soil and immediately identify the soil class from the trained model. The application can also recommend crops that are suitable for the soil type. This utilization of the mobile application can assist farmers to achieve higher crop yields by knowing the best crops for the particular soil type, resulting in higher crop productivity.

4. **Experimental Results and Discussion.** The accuracy of identification of the six different soil classifications is illustrated in Table 1. It shows that sand was identified with 99.5% accuracy, loam was 99% and clay was the lowest at 87.6%. The sand class has the best accuracy as it is distinctive in texture and color from the other classes of soil, as is loam. The accuracy rate of silty clay and clay classes was low as they are very similar in color and texture to other classes. Similarly, as discussed in [19], the proximity among classes makes distinguishing between them complex.

Table 1. The overall accuracy rate for each soil type

Soil type	Accuracy (%)
Clay	87.6
Silty clay	93.2
Sandy clay	87.8
Loam	99.0
Sandy loam	97.1
Sand	99.5

The deep learning models for soil classification such as Inception-v4, VGGNet-16, and ResNet50 illustrated in [16,17], have a running time cost that might not be suitable for employment in a mobile device that has fewer computational resources. MobileNet, which has a reduced number of layers, can be employed in a mobile application that is easy to use for quick analysis and convenient in smart farming for agriculturalists.

5. **Conclusions and Future Work.** The objectives of this research were to develop a deep learning model which can be employed on mobile devices, which is convenient for farmers to identify and classify their local area soil type from soil images taken in the field. While the accuracy of prediction of soil types in the model developed in MobileNet is lower than other deep learning models such as VGG16 [19], the tradeoff is having a faster, lightweight model which is suitable to be employed in a mobile application. The MobileNet model developed in this current research achieved a competent level of accuracy, indicating that the MobileNet deep learning model is effective in classifying soil types. However, further experiments in the field should be explored to further enhance the accuracy of the mobile application. The MobileNet model can also be applied as a crop plant recommendation system, matching appropriate crop plants with the local soil type. Future development of the model includes providing soil improvement recommendations for soil properties and quality that may otherwise be considered deficient or inappropriate. Different deep-learning architectures should be explored for comparison and further investigation is suggested to discover other methods for the identification of other relevant image parameters to increase the accuracy of soil type identification.

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