ISSN: 2230-9926

Available online at http://www.journalijdr.com

IJDR

International Journal of Development Research

Vol. 11, Issue, 09, pp. 49932-49938, September, 2021

https://doi.org/10.37118/ijdr.22669.09.2021

RESEARCH ARTICLE **OPEN ACCESS**

MORPHOMETRIC CLASSIFICATION OF SOIL AGGREGATES USING DEEP LEARNING WITHIN THE CONCEPT OF PRECISION AGRICULTURE

Claudia Liliana Gutierrez Rosas*[1], Admilson Irio Ribeiro[1] and Maria Tejada-Begazo[2]

[1]Post-Graduation Program in Environmental Sciences, Department of Environmental Engineering, Universidade Estadual Paulista/UNESP, Sorocaba, SP, Brazil; [2]Graduate Program in Electrical Engineering, Department of Automation and Electronic Systems, Paulista State University/UNESP, Sorocaba, SP, Brazil

ARTICLE INFO

Article History:

Received 18th June, 2021
Received in revised form
07th July, 2021
Accepted 20th August, 2021
Published online 27th September, 2021

Key Words:

Soil Aggregate, Convolutional Neural Network, Morphometry, Images.

Corresponding author:
Claudia Liliana Gutierrez Rosas

ABSTRACT

The Within the concepts of precision agriculture, this research sought to develop and evaluate an artificial neural network model capable of identifying and classifying different morphometric classes of aggregates through images. The methodology developed used a Convolutional Neural Network, with the application of MobileNetV2 architecture transfer learning in three experiments, Training with 5 morphometric classes (prismatic, angular, subangular, rounded and rounded), Training with 4 classes (prismatic, angular, subangular and rounded) and Training with 3 classes (prismatic, angular, rounded). During network development and data_set processing, sampling and data cleaning methods were used. The MobileNetV2 performance results for the three Trainings showed an average accuracy of 79%, with the Training with 3 classes performing best with an accuracy of 87%. In all three experiments, the morphometric classes with the highest accuracy were round, rounded and angular, while for prismatic and subangular classes the network showed a lower accuracy. It can be concluded that the preparation of the data set, the preprocessing in general, is a very important phase, as it can influence and make a difference in the performance of the network. For this it is necessary to have a robust dataset, in quality and quantity of images per class, in addition to hardware and software configurations, the more optimized this set is, the greater the likelihood of improvement in the accuracy of the classification of aggregates. This research constitutes a starting point for research related to the development of technologies and innovations for soil analysis.

Citation: **Claudia Liliana Gutierrez Rosas, Admilson Irio Ribeiro and Maria Tejada-Begazo, *2021.*** "Morphometric classification of soil aggregates using deep learning within the concept of precision agriculture", *International Journal of Development Research*, 11, (09), 49932-49938.

INTRODUCTION

The process of soil degradation is linked mainly to human pressure, such as population growth and the need to produce more food to maintain the population, thus presenting itself today, in most of the world, an intensive agriculture, which is causing structural and functional changes in the soil that condition its productivity (Anghinoni, Carvalho & Costa; 2013). Soil structure refers to the pattern of arrangement of primary particles (sand, silt, and clay) into structural units (peds or aggregates). Adhesion and cohesion forces and cementing agents are responsible for binding the primary particles together (BRADY & WEIL, 2009; RABOT et al., 2018). GUERRA et al. (2009), describes soil structure as a structural unit with a coherent set of primary soil particles with defined shape and size. Thus, different types of aggregates can exist within the same soil horizon, their presence can vary both horizontally and vertically.

Well aggregated soils offer better conditions for plant development, hence the importance of obtaining information about soil aggregates, such as size, shape, and stability (KOHN, 2017). In this scope, the analysis of the structural condition of the soil can be determined by the degree of aggregation of the primary soil particles, evaluating as one of the indicators the shape of the aggregates. The hierarchical organization of soil, has five groups of parameters: morphometric, geometric, physical, chemical and energetic (GERVASIO PEREIRA et al., 2019). At the morphometric level, soil aggregates range from the micro level (less than 0.25 mm in diameter) to the macro level (more than 0.25 mm in diameter). In addition, aggregates they can resemble various shapes: Round, round, prismatic, angular (SALTON et al., 2008; STEINBECK, 2006). These varied shapes allow healthy soil to have porous spaces for air and water, which are necessary for healthy plant growth (CASTRO FILHO et al., 1998; SALTON et al., 2008). According to FAUSTINO (2018), the morphometric analysis of aggregates is important because the geometry of aggregates interferes with pore diameter distribution, which modifies air, water, and soil nutrient dynamics and consequently affects plant root growth. There are different ways to evaluate the morphometry of aggregates mainly developed in pedology and civil engineering (LEÓN & RAMÍREZ, 2010), but little developed in the area of agriculture, the process is basically in three steps, the acquisition of images by scanner or cameras; then the analysis of the images to obtain morphometric characteristics or parameters; and finally, the interpretation of the results generated. In recent years the development of intelligent systems has become a very important tool to optimize the processes of evaluation of behaviors and patterns capable of assisting in decision making (CHITERO *et al.,* 2020). Thus, in the present research to evaluate and classify the shape of aggregates from digital images, Convolutional Neural Network was used, a class of deep artificial neural networks (*Deep Learning*), the most developed currently in the field of image classification, because they are the widely adapted for image classification and demonstrated high performance compared to other methodologies proposed so far (QUINTERO *et al*., 2018, AZIZI et *al.,* 2020).

A Convolutional Neural Network (CNN) is a type of bio-inspired network that simulates the way human vision works (SHARMA *et al.,* 2018). The name "convolution neural network" indicates that the network employs a mathematical operation called convolution instead of general matrix multiplication in at least one of its layers (TRAORE et al., 2018, DHILLON & VERMA, 2020). Soil structure refers to the pattern of arrangement of primary particles (sand, silt, and clay) into structural units (peds or aggregates). Adhesion and cohesion forces and cementing agents are responsible for binding the primary particles together (BRADY & WEIL, 2009; RABOT et al., 2018). GUERRA et al. (2009), describes soil structure as a structural unit with a coherent set of primary soil particles with defined shape and size. Thus, different types of aggregates can exist within the same soil horizon, their presence can vary both horizontally and vertically. Well aggregated soils offer better conditions for plant development, hence the importance of obtaining information about soil aggregates, such as size, shape, and stability (KOHN, 2017). In this scope, the analysis of the structural condition of the soil can be determined by the degree of aggregation of the primary soil particles, evaluating as one of the indicators the shape of the aggregates. The hierarchical organization of soil, has five groups of parameters: morphometric, geometric, physical, chemical and energetic (GERVASIO PEREIRA et al., 2019). At the morphometric level, soil aggregates range from the micro level (less than 0.25 mm in diameter) to the macro level (more than 0.25 mm in diameter). In addition, aggregates they can resemble various shapes: Round, round, prismatic, angular (SALTON et al., 2008; STEINBECK, 2006). These varied shapes allow healthy soil to have porous spaces for air and water, which are necessary for healthy plant growth (CASTRO FILHO et al., 1998; SALTON et al., 2008). According to FAUSTINO (2018), the morphometric analysis of aggregates is important because the geometry of aggregates interferes with pore diameter distribution, which modifies air, water, and soil nutrient dynamics and consequently affects plant root growth.

There are different ways to evaluate the morphometry of aggregates mainly developed in pedology and civil engineering (LEÓN & RAMÍREZ, 2010), but little developed in the area of agriculture, the process is basically in three steps, the acquisition of images by scanner or cameras; then the analysis of the images to obtain morphometric characteristics or parameters; and finally, the interpretation of the results generated. In recent years the development of intelligent systems has become a very important tool to optimize the processes of evaluation of behaviors and patterns capable of assisting in decision making (CHITERO *et al.,* 2020). Thus, in the present research to evaluate and classify the shape of aggregates from digital images, Convolutional Neural Network was used, a class of deep artificial neural networks (*Deep Learning*), the most developed currently in the field of image classification, because they are the widely adapted for image classification and demonstrated high performance compared to other methodologies proposed so far (QUINTERO *et al*., 2018, AZIZI et *al.,* 2020). A Convolutional Neural Network (CNN) is a type of bio-inspired network that simulates the way human vision works (SHARMA *et al.,* 2018). The name "convolution neural network" indicates that the network employs a mathematical operation called convolution instead of general matrix multiplication in at least one of its layers (TRAORE et al., 2018, DHILLON & VERMA, 2020). The architecture of a CNN is composed of several two-dimensional planes, and each plane consists of several independent neurons (SHARMA et al., 2018). By the rapid development of CNNs, many powerful architectures have emerged, such as the classical LeNet model for AlexNet, ZFNet, GoogleNet, VGGNet, MobileNet , ResNet, SENet, DenseNet, etc., each with different levels of development and complexity, and the number of parameters used (MAEDA-GUTIÉRREZ et al., 2020; SUDEEP & PAL, 2017). Its main elements, are the *input* layer (*Input image*), output layer (*Output layer*) and several hidden layers, where the hidden layer mainly consists of three types, the convolutional layer (*Convolutional layer)*, pooling layer (*Pooling layer)* and fully connected layer (*Dense layers*) a (GUO et al., 2017; TRAORE et al., 2018; DHILLON & VERMA, 2020). For developing a CNN, the Keras module provides a convolutional layer for images, called Conv2D, and other *layers* (or *layers*) to use in sequential combination, such as *MaxPooling2D, Dropout, Flatten, Dense, and Activation.* The pooling layer is used to reduce dimensionality by associating the output of the cluster of neurons in a layer with the single neuron. And the fully connected layer's main function is to classify the input images into various classes based on the training datasets (DHILLON & VERMA, 2020). In this scope, to perform soil evaluation through images within the concepts of *deep learning* applicability, developing a convolutional neural network model to detect and classify the different forms of soil aggregates, is to optimize the soil evaluation process for its management, within the concept of precision agriculture.

MATERIALS AND METHODS

The present research was developed in 2020. For the development of the methodology steps, a notebook computer with a 64-bit Windows 10 operating system and an Intel Core i5 processor was used.

Data Set Generation: The database, digital images of the soil aggregates, were made available through the visual analysis database conducted by PECHE FILHO (2018). The aggregates are of agricultural origin and were photographed using a digital microscope, Dino Lite, model AM211. A survey of image properties was performed, these were standardized, organized and then evaluated with ImageJ software to obtain quantitative data, such as Feret diameter, roundness, area and circularity Considering for example the roundness, in equidistant intervals, and assigning a range of values for shape classes (0 to 0.2 - prismatic; 0.2 to 0.4 -angular, 0.4 to 0.6 - subangular, 0.6 to 0.8 - rounded, 0.8 to 1.0 - round). The visual evaluation method was also employed, according to the shape pattern, to make the necessary adjustments to the different folders of previously classified images. The dimensions of the original images were checked, then the images were resized to the size 480 x 480 x 3, thus standardizing all the images in the database and the segmentation (to exclude the background). To add the database from the training set, the *data_augmentation* procedure was performed, mirroring the original and rotated images (90, 180 and 270 degrees). With the procedure, from 4350 unique images 30450 images were generated.

CNN Development: After acquiring the images and having them organized in data_set, 80% of them were used for training the neural network, 20% for the validation set, and another 200 images for the test set. The Spyder IDE was used to organize the files and develop the project and algorithm programming in Python. Also, the open source TensorFlow and Keras machine learning libraries were used. TensorFlow can train and run deep neural networks for image classification (Tensor Flow, 2020). The CNN model developed was the MobileNetV2, which uses the ImageNet data_set. This network makes it possible to perform transfer learning, which is a method that allows you to train your own models by reusing the network structure (PUJARA, 2020, HOWARD *et al.* 2017). In order to further evaluate the performance of the MobilenNetV2 model, 3 types of training were used, Training with 5 classes, Training with 4 classes, and Training with 3 morphometric classes of soil aggregates, each evaluated with the performance metrics of a neural network. The number of epochs for the three Trainings was 20. Regarding epochs, if there are too few, the network cannot express its maximum learning, i.e., underfitting. However, many epochs, the opposite problem can occur, overlearning also called overfitting (ARTOLA, 2019). Training was performed with 10, 15, 20 and 50 epochs, but the results were better with 20 epochs and 32 batch_size. The batch_size 32 is suitable for most systems (CPUs).

Training with 5 classes: The data set is illustrated in Figure 1, with the following values: round (1980), rounded (8500), sub-angular (9200), angular (7902), prismatic (2868). For a total of 30450 images.

Training with 4 classes: In order to improve the network performance, after evaluating the model of Training with 5 classes, it was decided to perform *Under sampling* (balancing the amount of images per class) and *data cleaning* (cleaning of data that may negatively impact the model). Thus, the data set is illustrated in Figure 2, with the following values: round (2500), sub-angular (2500), angular (2500), prismatic (2500). With a total of 10000 images.

Training with 3 classes

The *data_set* was organized into classes in an extremes condition (Figure 3), with the following values: round (2500), angular (2500), and prismatic (2500). In total 7500images.

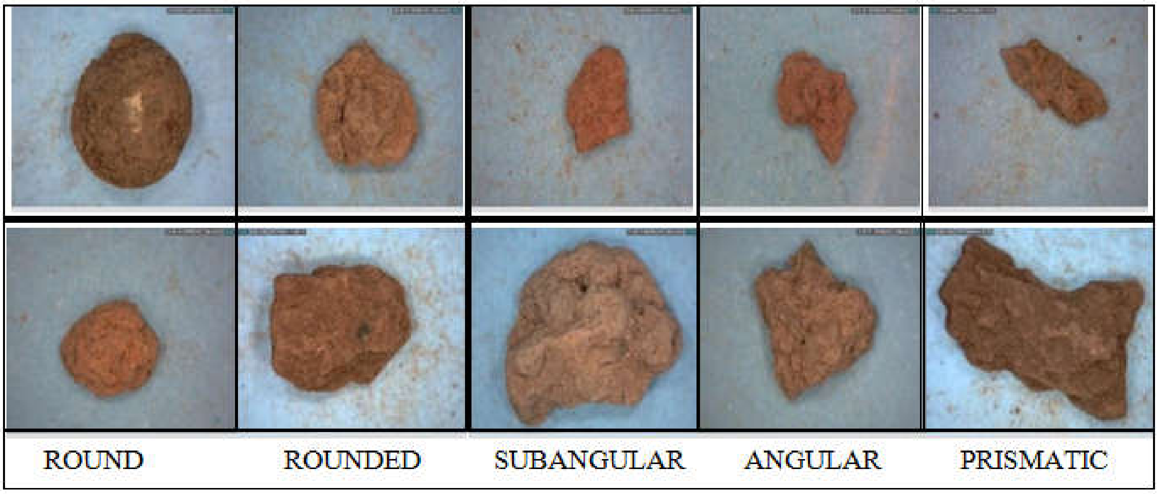

Figure 1. Classification of aggregates in 5 classes

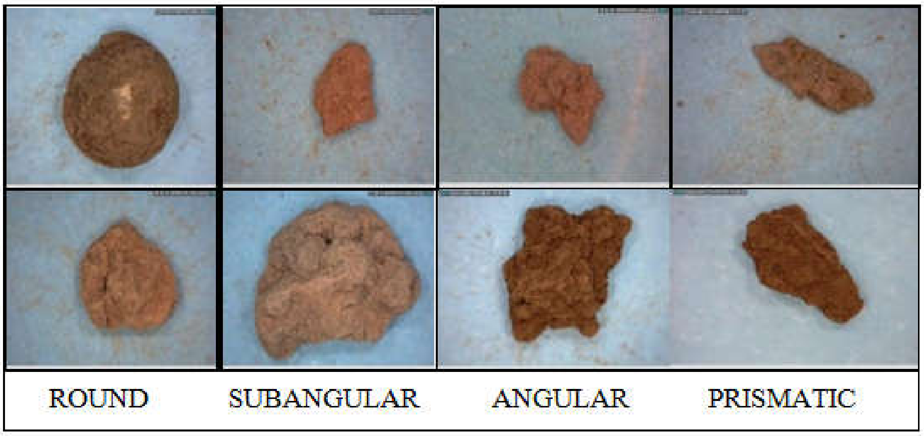

Figure 2. Classification of aggregates in 4 classes

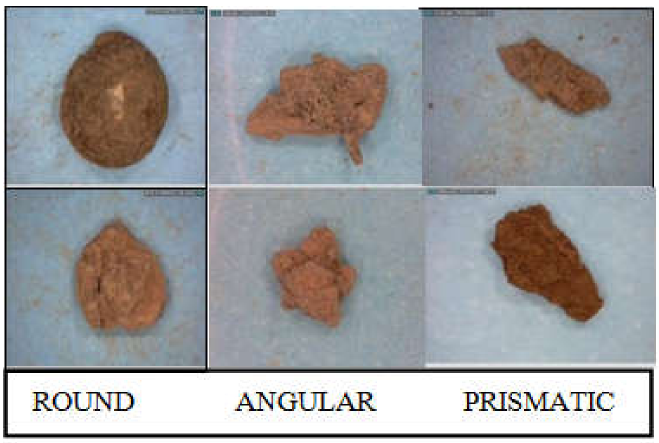

Figure 3. Classification of aggregates in 3 classes

After selecting, implementing, and training a neural network model, the next step was to evaluate how good the network would be at predicting future values. The performance evaluation was done using a confusion matrix. The confusion matrix relates the prediction to the actual or true answer. The elements of the matrix represent the relationships between prediction and classification reality for each class: A true positive (VP) happens when the real, class was predicted correctly. A false positive (FP) happens when the prediction was incorrect with the actual class is true and in reality, it is false; a false negative (FN) happens when the prediction is false and in reality, it is true; a true negative (VN) happens when the prediction is false and so is the reality so that the rows indicate what the predicted patterns, while the columns indicate the actual responses (ARTOLA, 2019). Table 1 shows a confusion matrix.

Table 1. Confusion matrix

Expected Value / True Value	Positive	Negative
Positive	True Positive (VP)	False Negative (FN)
Negative	False Positive (FP)	True Negative (TN)

The quadrants in blue are the hits, and the ones in white are the misses. From these 4 values the other important metrics are calculated, such as *Accuracy*, *Precision*, *Recall, and F1 score* (ARTOLA, 2019).

Accuracy measures the percentage of cases where the model has been correct.

$$Accuracy = \frac{VP+VN}{VP+FN+FP+VN} \quad (1)$$

The *Precision* metric represents the ratio between the actual positives predicted by the algorithm and all positive cases.

$$Precision = \frac{VP}{VP+FP} \quad (2)$$

The *Recall* metric is the proportion of positive cases that were correctly identified by the algorithm.

$$recall = \frac{VP}{VP+FN} \quad (3)$$

The *F1 score* metric combines *Precision* and *Recall* into a single measure.

$$F1\ score = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (4)$$

The "*loss*", on the other hand, is a sum of the errors made for each example in training or validation sets. It shows how far you are from the 'ideal' solution. The smaller the loss, the better the model.

RESULTS AND DISCUSSIONS

The results of the neural network learning metrics for the cluster shape classification in Training with 5 classes, Training with 4 classes, and Training 3 with classes are presented in Figure 4. The *accuracy* for Training with 5 classes was 73% and a loss of 0.87. The performance of this first Training was affected by the problem of image heterogeneities and the unbalanced number of images per class. As for the Training with 4 balanced classes, using the *Under-Sampling* and *data cleaning* methods*, a* significant improvement in the classification performance is noticed, with an *accuracy* of 79%, but with a loss of 0.99, a value higher than the Training with 5 classes.

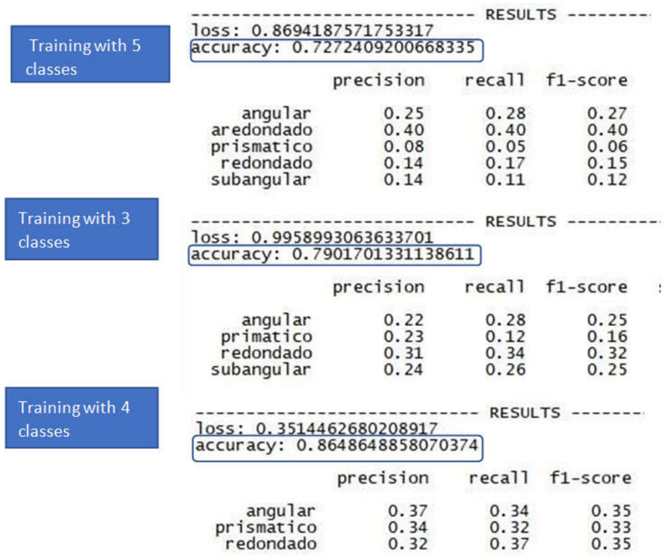

Figure 4. Neural network performance metrics from the three Trainings

However, the quantification metric of accuracy for each class also resulted with more similar percentages, being higher for the rounded class and lower for the prismatic class. The network performance of Training 3 with 3 classes performed better compared to Training 5 classes and Training 4 classes, with an *accuracy of* 86% (Figure 4). For Training with 3 classes, it was possible to graph the network's performance, relating *loss* and *accuracy to the* training epochs (Figure 5). The biggest difference was in the loss rate, which was 0.36, a value lower than the loss rate of previous trainings. This improvement may be due to the better quality of the *data_set,* but the decrease in the number of images per class may have influenced the net learning process.

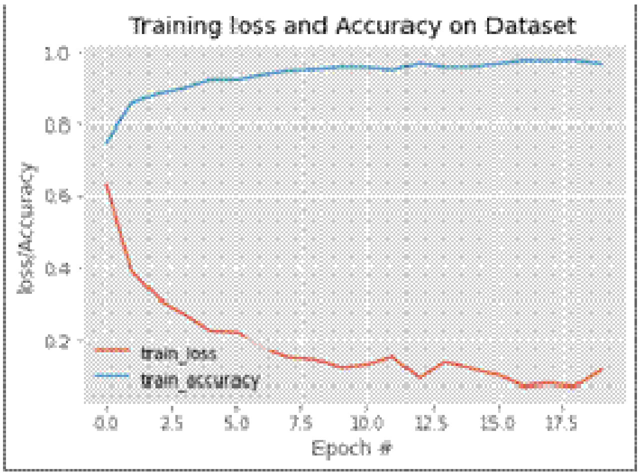

Figure 5. Graph of the neural net training with 3 classes

The analysis of the learning performance in the confusion matrix metrics of the 5-class training (Figure 6), shows a better performance (accuracy) of the network in the classification of the Rounded and Angular classes, which were the classes with the highest number of images. The class that showed lower accuracy was the prismatic class, this may be related to the fact that the class had the fewest number of images for training and validation with respect to the other classes. The learning performance of the CNN with 5 classes was low, due to the unbalanced amounts of images for each class. For the best performance of the network, it is ideal that all classes are balanced, for uniform learning based on the same metrics, for this it is important to use the *Under-Sampling* method. However, there may be the need for a larger number of images, because the use of morphometric classes of similar aggregates with the visual analysis methodology, requires more information for a better classification and learning of the network (RODRIGUEZ, 2018).

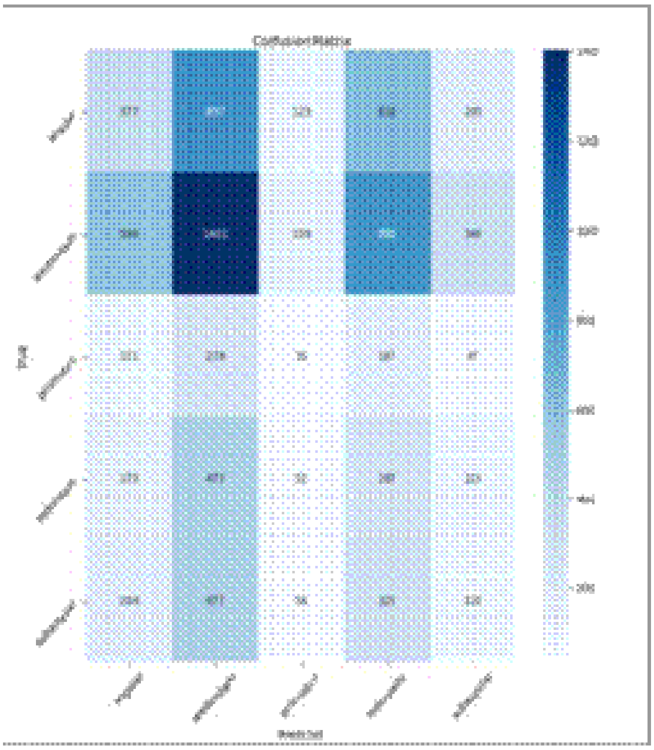

Figure 1. Confusion matrix with 5 classes

Figure 7 illustrates the CNN performance in the identification and classification of soil aggregates in the 4-class training, indicating in blue the correct answers (True Positive) and in red the no-answers (False Positive/False Negative). Within the confusion matrix analysis of the 4-class training, a better performance of the network is observed in the classification of the Round, Subangular and Angular classes. However, the accuracy for the Prismatic class is still low, because Figure 8 shows a higher amount of false positives and false negatives with the other three classes.

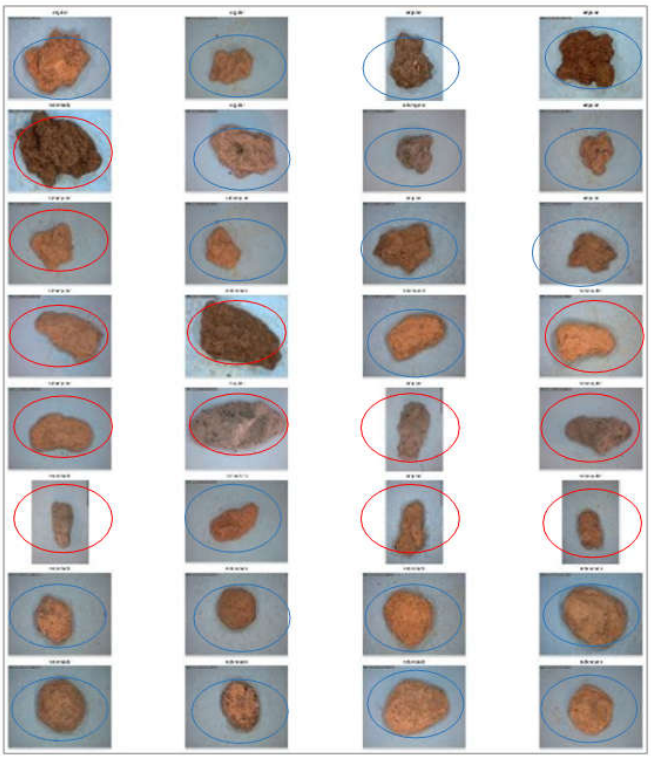

Figure 7. Identification and classification of the Training network with 4 classes

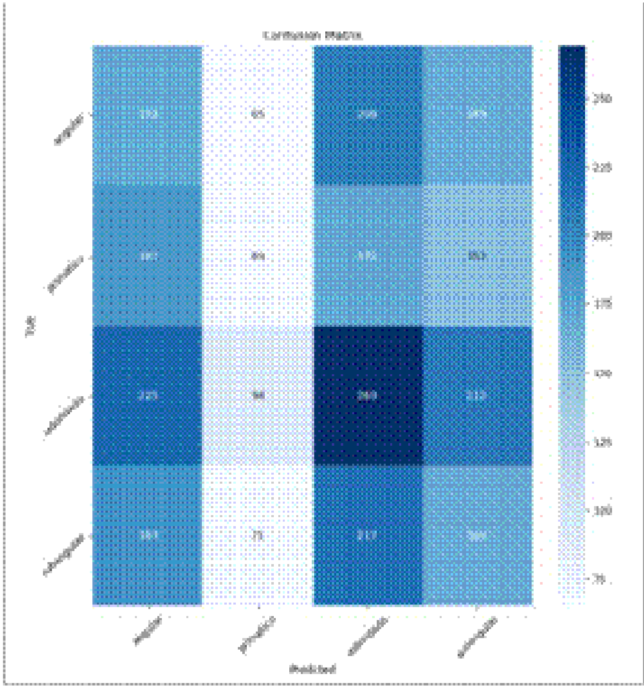

Figure 8. Confusion Matrix with 4 classes

In the confusion matrix analysis of Training with 3 classes, a better accuracy in the classification of the Round and Angular classes is observed. While for the Prismatic class there is an improvement in accuracy, Figure 9 shows a higher amount of true positives compared to Training with 5 classes and Training with 4 classes.

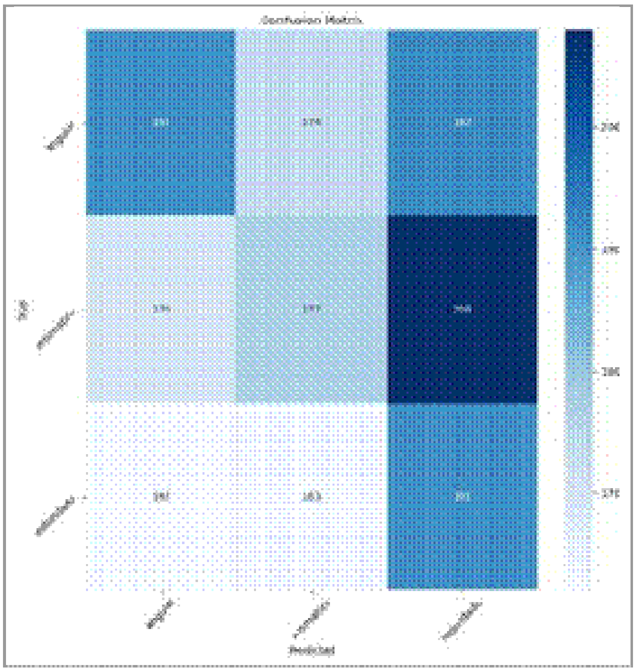

Figure 9. Confusion Matrix with 3 classes

In the three Trainings with the MobileNetV2 model the average *accuracy* was 79.3%, and the highest *accuracy* reached was with the Training with 3 morphometric classes (86%), values similar to the *accuracy* of *86%* reached by a multilayer ANN model developed to estimate the stability index of soil aggregates with numerical data by MARACHI *et al*. (2017) and an *accuracy of* 73.81% of a classifier based on artificial neural networks to generate a map with different soil classes through the analysis of digital satellite images developed by CHAGAS *et al*. (2013). But the results obtained are lower compared to the *accuracy* achieved by the CNN models VggNet16, ResNet50 and Inception-v4, worked by AZIZI *et al.* (2020) using stereo images to classify the aggregates by size, with an average *accuracy of* 95% being the highest *accuracy* achieved with the ResNet50 architecture (98.72%). The method used for the study of soil aggregates through digital images has its advantages and disadvantages, one advantage of this method of soil evaluation through imaging is that the aggregate, for example, does not undergo physical, chemical or biological changes compared to the analysis in traditional laboratories (Padarian, Minasnya & Mcbratneya, 2018), but suffer from limitations such as software, hardware, quantity and quality of image acquisition, in addition to the degree of subjectivity in image processing protocols, the extraction of features, and the requirement of some level of user information in terms of training data and deep learning (SCHLÜTER *et al.* , 2020), thus influencing performance in the results of the neural network. CNNs have multiple uses and many potential applications in image classification in different areas of human knowledge, but it is important to note that effective machine learning techniques usually require a lot of data for training (YEN & LEE, 2006). From Training with 5 classes (30450 images) to Training with 3 classes (9220 images) the amount of images for training and validation decreased, due to processing and methods to improve the quality of the *data_set*. A larger database, after pre-processing, balancing methods, and homogenization of the quantity of images per class, allows for a better quality data_set for net training. Regardless of the low learning performance of the exemplified neural network, whether Training with 5 classes, Training with 4 classes, and Training with 3 classes, the research presents a promising future, because the neural network can be trained to recognize and analyze parameters such as aggregate roughness, shape, color, size, biogenic activity, among others, being of great contribution to the development of new technologies for soil structural management in a remote and intelligent way.

CONCLUSIONS

The evaluation of the MobileNetV2 model neural network learning for the three Trainings showed an average *accuracy of* 79%, being most satisfactory for the morphometric soil aggregate classification of the rounded and angular classes. The use of *data_augmentation, Under sampling* and *data_cleaning* methods influence the performance results, methods used for Training with 4 classes and Training with 3 classes, where the MobileNetV2 network achieved an *accuracy of* 86%. The preparation of the *data_set* consists of a very important phase, as was analyzed in the three Training of the research. This preparation can make the difference in the learning performance of the network, because it is associated with the following factors: quality and quantity of images per class, pre-processing strategy in general, choice of hardware and software, and the level of knowledge of the object under study.

REFERENCES

Anghinoni, I., Carvalho, P. D. F., & Costa, S. D. A. (2013). *Systemic approach to soil in integrated crop and livestock production systems in the Brazilian subtropics*. Topics in Soil Science, 8(2), 325-380.

Artola, Á. (2019). *Clasificación de imágenes usando redes neuronales convolucionales en Python* [Escuela Técnica Superior de Ingeniería Universidad de Sevilla]. Http://bibing.us.es/proyectos/abreproy/92402/fichero/TFG-2402-ARTOLA.pdf

Afshin Azizi, Yousef Abbaspour Gilandeh, Tarahom Mesri-Gundoshmian, Ali Akbar Saleh-Bigdeli & Hamid Abrishami Moghaddam (2020). Classification of soil aggregates: A novel approach based on deep learning. Soil and Tillage Research,Volumen 199, 104586,ISSN 0167-1987. Https://doi.org/10.1016/j.still.2020.104586.

Brady, N. C., & Weil, R. R. (2009). Elements of the nature and properties of soils. Bookman Editora.

Castro Filho, C., Muzilli, O., & Podanoschi, A. L. (1998). *Aggregate stability and its relationship with organic carbon content...* 527 Aggregate stability and its relationship with organic carbon content in a dystrophic purple latosol as a function of planting systems, crop rotations and sample preparation methods *(1)* (Vol. 22).

Chagas, C. Da S., Vieira, CAO, & Fernandes Filho, EI (2013). Comparison between artificial neural networks and maximum likelihood classification without digital soil mapping. Brazilian Journal of Soil Science, 37 (2), 339-351. Https://doi.org/10.1590/S0100-06832013000200005

Chitero, Jgm; Bonini Neto, A.; Bonini, C. Dos Sb; Heinrichs, R.; Soares Filho, Cv; Mateus, Gp; Bisi, Bs; Costa, Nr; Piazentin, Jc; Meirelles, Gc; Gabriel Filho, Lra Analysis of the physical recovery of degraded soils via Artificial Neural Networks using a graphical interface. Research, Society and Development, [S. L.], v. 9, n. 7, p. E257973719, 2020. DOI: 10.33448 / rsd-v9i7.3719. Available at: https://rsdjournal.org/index.php/rsd/article/view/3719. Accessed on: 26 Jan. 2021.

Dhillon, A., & Verma, G. K. (2020). Convolutional neural network: a review of models, methodologies and applications to object detection. In *Progress in Artificial Intelligence* (Vol. 9, Issue 2, pp. 85-112). Springer. Https://doi.org/10.1007/s13748-019-00203-0

Luís Faustino (2018). Indicators of the physical and morphological quality of a Red- Yellow Argissolo in pasture areas revegetated by tree legumes /Thesis (PhD in Plant Production) - Universidade Estadual do Norte Fluminense Darcy Ribeiro, Centro de Ciências e Tecnologias Agropecuárias, 125. https://uenf.br/ccta/lsol/files/2018/06/Lucas-Faustino-Prof.-Cl%C3%A1udio.pdf

Howard, A. G., Zhu, M., Chen, B., Kalenichenko, D., Wang, W., Weyand, T., Andreetto, M., & Adam, H. (2017). Mobilenets: Efficient convolutional neural networks for mobile vision applications. In *arxiv*. Arxiv. Https://arxiv.org/abs/1704.04861v1

Gervasio Pereira, M., Helena Cunha dos Anjos, L., Roberto Pinheiro Junior, C., Alberto da Silva Rodrigues Pinto, L., Carvalho da Silva Neto, E., & Fontana, A. (2019). *CHAPTER 1 SOIL FORMATION AND CHARACTERIZATION.*

Guo, T., Dong, J., Li, H., & Gao, Y. (2017). Simple convolutional neural network on image classification. *2017 IEEE 2nd International Conference on Big Data Analysis, ICBDA 2017*, 721-724. Https://doi.org/10.1109/ICBDA.2017.8078730

Guerra, A. T., da Silva, A. S., & Botelho, R. G. M. (2009). Erosão e conservação dos solos: conceitos, temas e aplicações. Bertrand Brazil.

Kohn, L. S. (2017). Morphometric analysis of aggregates of a Humic Cambisol under flax cultivation and its root development.

León, M. P., & Ramírez, F. (2010). Morphological characterization of concrete aggregates by means of image analysis. *Revista Ingeniería de Construcción*, *25*(2), 215-240. https://doi.org/10.4067/S0718-50732010000200003

Maeda-Gutiérrez, V., Galván-Tejada, C. E., Zanella-Calzada, L. A., Celaya-Padilla, J. M., Galván-Tejada, J. I., Gamboa-Rosales, H., Luna-García, H., Magallanes-Quintanar, R., Guerrero Méndez, C. A., & Olvera-Olvera, C. A. (2020). Comparison of Convolutional Neural Network Architectures for Classification of Tomato Plant Diseases. *Applied Sciences*, *10*(4), 1245. Https://doi.org/10.3390/app10041245

Maryam Marashi, Ali Mohammadi Torkashvand, Abbas Ahmadi & Mehrdad Esfandyari (2017). Estimation of soil aggregate stability indices using artificial neural network and multiple linear regression models. Spanish Journal of Soil Science: SJSS, ISSN-e 2253-6574, Vol. 7, No. 2, 2017, pp. 122-132

Padarian, J., Minasny, B., and McBratney, A. B.: Using deep learning for digital soil mapping, SOIL, 5, 79-89, https://doi.org/10.5194/soil-5-79-2019, 2019

PECHE FILHO, A. (2018). Aggregation variability in agricultural soil samples as a quality indicator: a methodological proposal. Thesis doctoral. Paulista State University "Júlio de Mesquita Filho"

PUJARA, A. (2020, July 4). *Convolutional neural network mobilenet Machine learning algorithms | Analytics Vidhya*.

Https://medium.com/analytics-vidhya/image-classification-with-mobilenet-cc6fbb2cd470

Quintero, C., Merchán, F., Cornejo, A., & Galán, J. S. (2018). Uso de Redes Neuronales Convolucionales para el Reconocimiento Automático de Imágenes de Macroinvertebrados para el Biomonitoreo Participativo. Kne Engineering, 585-596.

Rabot, E., Wiesmeier, M., Schlüter, S., & Vogel, H. J. (2018). Soil structure as an indicator of soil functions: A review. In *Geoderma* (Vol. 314, pp. 122-137). Elsevier B.V. https://doi.org/10.1016/j.geoderma.2017.11.009

Rodriguez, V. (2018, October 30). *Basics of neural network*. Https://vincentblog.xyz/posts/conceptos-basicos-sobre-redes-neuronales

Salton, J. C., Mielniczuk, J., Bayer, C., Boeni, M., Conceição, P. C., Fabrício, A. C., Macedo, M. C. M., & Broch, D. L. (2008). Soil aggregation and aggregate stability under crop- pasture systems in Mato Grosso do Sul state, Brazil. *Revista Brasileira de Ciência Do Solo*, *32*(1), 11-21. Https://doi.org/10.1590/s0100-06832008000100002

Sharma, N., Jain, V., & Mishra, A. (2018). An Analysis of Convolutional Neural Networks for Image Classification. Procedia Computer Science, 132, 377-384. Https://doi.org/10.1016/j.procs.2018.05.198

Sudeep, K. S., & Pal, K. K. (2017). Preprocessing for image classification by convolutional neural networks. 2016 IEEE International Conference on Recent Trends in Electronics, Information and Communication Technology, RTEICT 2016 - Proceedings, 1778- 1781. Https://doi.org/10.1109/ RTEICT.2016.7808140

Steffen Schlüter (2019): Exploring the relationship between soil structure and soil functions via pore-scale imaging," Martin Luther University Halle-Wittenberg, Germany. https://doi.org/10.1016/j.geoderma.2020.114370

Steinbeck, J. V. (2006). Architecture and Physical Properties of Soil. Https://edisciplinas.usp.br/ pluginfile.php/917327/mod_resource/content/2/Apostila%20-%20Architecture%20and%20Properties%20F%C3%adscas%20of%20Soil.pdf

Tensorflow. (2020). Https://www.tensorflow.org/

Traore, B. B., Kamsu-Foguem, B., & Tangara, F. (2018). Deep convolution neural network for image recognition. Ecological Informatics, 48, 257-268. Https://doi.org/10.1016/j.ecoinf.2018.10.002

Yen SJ, Lee YS. (2006) Under-Sampling Approaches for Improving Prediction of the Minority Class in an Imbalanced Dataset. In: Huang DS, Li K, Irwin GW (eds) Intelligent Control and Automation. Lecture Notes in Control and Information Sciences, vol. 344. Springer, Berlin, Heidelberg. Https://doi.org/ 10.1007/978-3-540-37256-1_89

****