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CLASSIFICATION OF SOIL PROPERTIES FROM HYPERSPECTRAL DATA USING DENSENET-169+

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Abstract

Accurate and effective mapping of soil properties is regarded as a critical task in environmental and agricultural management. The evaluation of properties of soil is a daunting task while monitoring and sensing the environment. Existing image process methods are time-consuming and they are limited with regions and classification its training layer. However, the need of soil analysis and its properties is essential at landscape level. In this paper, DenseNet-169+ used to assess the soil properties via its classification task from real-input images. The DenseNet-169+ studies the variability index of the soil using Kriging interpolation technique. The simulation is conducted to study the efficacy of the model under different soil conditions and the efficacy of DenseNet-169+ is reported. The results of simulation show that the proposed method achieves higher rate of classification accuracy than other models.

Keywords:
DenseNet-169+, Soil Properties, Deep Learning, Prediction

1. INTRODUCTION

Soil classification is one of the major specializations in productive research, ranging from the system composition to the field application [1]. The interest of research in the soil classification including its texture and colour classification has increased due to the availability of the digital methods for soil imaging [2]. Conventional methods for soil classification are applied in different laboratories and fields. Engineers usually classify soils according to their engineering characteristics [3] [4].

Recent classification systems have allowed an easy transformation from the fundamental field survey to the properties/behaviour of soil engineering. The images produced in soil sections via a digitisation process, using conventional cameras, microscopes, or polarised light scanners, show a considerable range of geometric features [5]. Soil classification can be considered as a resource, where the perspective of soil is obtained from the soil as a “material”. The soil is the spreading part of the rubble or remains of a mining engineer enclosing the minerals or rocks he extracts or mines. The land is to be placed on a track bed for highway engineering.

Soil characteristics play an important role in the evaluation of various tasks associated with agriculture, which has an impact on agricultural engineering. Understanding land properties can provide useful data to develop a precise management system and utilizing it for the purpose of cultivation. The geology, biota and climate are key issues that excessively affect both the chemical and physical properties of the soil, whilst human activities and topography control are dominating factors. Basic components of soil include discrete fragments of plants that can be seen by optical microscopes in disintegration. Soil structure is directly linked to sharpness, shape, frequency of contrast, size, voidness, and spatial arrangement of key particles. In addition, many of these characteristics depend on the alignment of the components as well as on how they are cut and magnified [6].

Various methods for determining soil colour and texture are traditionally available. The elutriation, pipette, decantation, and colour chart method are numerous methods for laboratory and field use. The downfall is that these conventional models are processes that take time and cost [7]. Therefore, researchers focused on soil classification by using computer vision methods to classify soil. Rural farmers have little knowledge or information about the texture with regard to field study. With very little pre-testing and are not aware of the choice of soil based on the crops the farmer wish to cultivate. The overall growth of plants is affected by this. Farmers, therefore is allowed to get equipped with a solution free of trouble, which provides them with information on the soil that they use to grow crops [8].

In recent years, various computer-based algorithms are suggested other than conventional methods. Soil classification are carried out on the basis of different soil qualities, such as colour, texture, and particle size. In order to achieve an elaborate soil classification, soil maps can also be created using information such as vegetation and topography as soil covariates. In addition to soil classifying, such methods can also be used without human intervention in determining the soil pH index and laying quality. Depending on the manual or auto-generated features via the output of a deep neural network, classification of soil can be carried out in using two streams based on the current scenario [9].

In this paper, used DenseNet-169+ to assess the soil properties via its classification task from real-input images. The DenseNet-169+ studies the variability index of the soil using Kriging interpolation technique [10].

2. LITERATURE STUDY

The first is computer vision-based soil classification and image processing. First, a camera configuration creates a soil image database. Second, segmentation is used when it is necessary to divide the region of interest. Thirdly, different texture and colour characteristics are extracted. Finally, a pretrained classifier generates results with extracted characteristics.

Deep learning is an application of machine learning that provides numerous computer vision-processing studies and the provision of enormous data. Adaptive feature selection can be used to reduce dimensionality and enhance precision. The high discrimination characteristics [11, 12], low correlation [13] and high precision [14] to choose from. The selected features keep their original shapes, so the features values can be observed easily. For soil classification, several features can be used, including colour, texture, and shape. Therefore, methods for reduction of dimensionality can be included to improve precision. The reduction in dimensionality can be divided into two classes:

subspace selection and functional selection. Subspace methods including Linear Discriminant Analysis (LDA), Random Projection (RP), Principal Component Analysis (PCA), etc. Here, the RP can be applied directly for testing than conventional LDA and PCA, and is thus much faster. Certain extensions of RP including 2DRP [15], Sparse RP [16], 2DRP [17], which require considerably less computer complexity and cost of storage than conventional 1DRP.

To refine the details of object for instance segmentation, Zhang et al. [18] developed a R-CNN. The effects of semantic segmentation on instance segmentation are learned. It is said that this method is easily implemented and performed. Chu et al. [19] presented a multi-Layer Method Fusion algorithm for occluded and small objects. 3D-CNN soil classification systems proposed by Yu et al. [20] to explore tunable filters. Using a compressive sensing procedure, hyperspectral images of the soil have been restored with better resolution for space and spectral areas. The main component analysis is employed in the spectral domain to reduce the dimensionality.

Azizi et al. [21] suggested a study using in-depth learning to classify random soil aggregates within individual classes. In this case, CNN was used from a range of deep learning algorithms. In addition to this, the model was also trained by architects ResNet50, Inauguration-v4 and VggNet16. The highest accuracy of ResNet50 is 98.72%, compared to over 95% in network classification accuracy.

The dependence on spatial form designs and preparation techniques is largely diminished by the use of profound learning applications by facilitating the whole process of inserting images. The convolutional neural network (CNN) has been demonstrated as an accepted model among the various deep learning concepts. In CNN, the insertion into the hidden layers is directly converted into the inventory of the function maps. Each characteristic map of the softmax algorithm is defined as belonging to a specific level. Sometimes, deep learning and image processing, are used together to produce better results. For example, with statistical measures and with a vector machine supported, colour, texture, and form are analysed and classified [22]. In soil classification, certain methods implemented with deep learning in other areas may also be utilised. A method of colour classification of medical images was introduced by Yang et al. [23], which is very important in clinical examination. This work uses CNN-StoolNet for the classification task. The exactness was 97.5% with a low cost for the work presented. Leng et al. [24] used a light-weight framework for CNN for use in real-life hospitals. This research has shown a 98.40% accuracy rate with low computer complexity and storage.

3. METHODS

In this paper, DenseNet-169+ used to assess the soil properties via its classification task from real-input images. The DenseNet-169+ studies the variability index of the soil using Kriging interpolation technique.

The objective is to classify the soil images to identify the nature of soil for appropriate growth of a crop using strong prediction models. The soil images to be classified is of 6 kinds: clay, sand, gravel, Organic Carbon content, Cation Exchange Capacity, Nitrogen Content, pH level in water, and Sand Particle. where the availability of water in image is marked as 0. The images were captured from continuous reflectance spectra from 400 nm to 2500 nm called as hyperspectral data with the resolution of applied sensor is 0.5 nm.

(a) Sand (b) Gravel (c) Clay

Fig.1. Soil Types considered for the study

The list of images prepared is shown in Figure 1. A total of 2,000 frames served for the purpose of training the classifier with 500 frames are utilised for testing.

3.1 PARAMETERS USED

The soil images are trained using DenseNet-169+ with Kringing Interpolation method. Each parameter was then specified as indicated in Table.1.

Table.1. Parameters chosen for simulation

Parameters	**Value**
Iterations	90
Batch Size	32
Learning coefficient	$1e^{-6}$
Image size	56×56
Momentum	0.9
Learning rate step size	30
Learning rate	0.1
Weight decay	$1e^{-4}$
Learning rate gamma	0.1

The DenseNet-169+ initially learns the data characteristics and finishes the learning when the accuracy has increased moderately. If training sessions lead to overlearning, the process will be completed in less than 90 or 80 sessions. Furthermore, sample training data is effectively increased. Overlearning, firstly, means that the models are optimised with limited variations for sample data. It is therefore vital to note that the over-learning is suppressed by increasing as much as possible the sample data variation and reducing the unknown variations in the DenseNet-169+ model.

In addition, the total pixels is reduced in order to limit the processing burden on the programme. The image was then processed in this study to be 56×56 pixels in size. As for the number of pixels, the DenseNet-169+ at times fails in recognizing the sand and gravel characteristics when it first learned with 26×26 pixels. Following this, an improvement in sand-gravel discrimination was found when the size is modified to 56×56 pixels. Therefore, images of 56×56 pixels were finally used for learning.

3.2 FEATURE DETECTION

In convolutional layer, the image feature is detected (conv1). First of all, faster images are countless squares of slightly different colours. The image is then resized and processed in this study at 56×56 pixels, and 56×56 squares are lined up to take into account. For red, green, and blue, every pixel is considered between the 0-255 and it is then converted into grayscale study. The pixels are thought to be 56x56 inches between 0 and 255.

After convolution, work is carried out on each pooling layer to blur the image characteristics. Here, every 2×2 pixel from the edge of each pooling layer, numerical data for image entries is compressed to 1×1 pixel. The data in the output is 2×2 pixels, if 4×4 image is processed. The presence of pooling layer halves the total number of number of pixels in an image.

After the image features are detected in those layers, Softmax function finally converts the output of the neural network to the probability of calculating which error tends to occur between the DenseNet-169+ preview and the true image value. If the model shows an image of sand, the true value obtains is labeled as "sand", and if the results of DenseNet-169+ are sand, the obtained results are considered accurate and vice versa. Therefore, the connection weight is updated based on the calculated error following those processes.

3.3 DENSENET-169+ CLASSIFICATION

DenseNet-169+ is a type of neural network that uses dense links from layers via dense blocks, where the study directly connects the entire layers (with its respective feature-maps). Every layer gets further inputs from all previous layers and passes its own feature maps with its consecutive layers to preserve the nature of classifier.

Consider a single image x_0 via the initial layer of the network i.e. convolutional network. The DenseNet-169+ network is designed with L layers or strata, where each layer adopts a non-linear $H^l(\cdot)$ transformation, in which the l layers are considered as indexed. The composite function $H^l(\cdot)$ of such operations including convolution, pooling, rectified linear units and batch normalization. The study indicate 'lth layer' output as x_l.

3.4 RESNETS

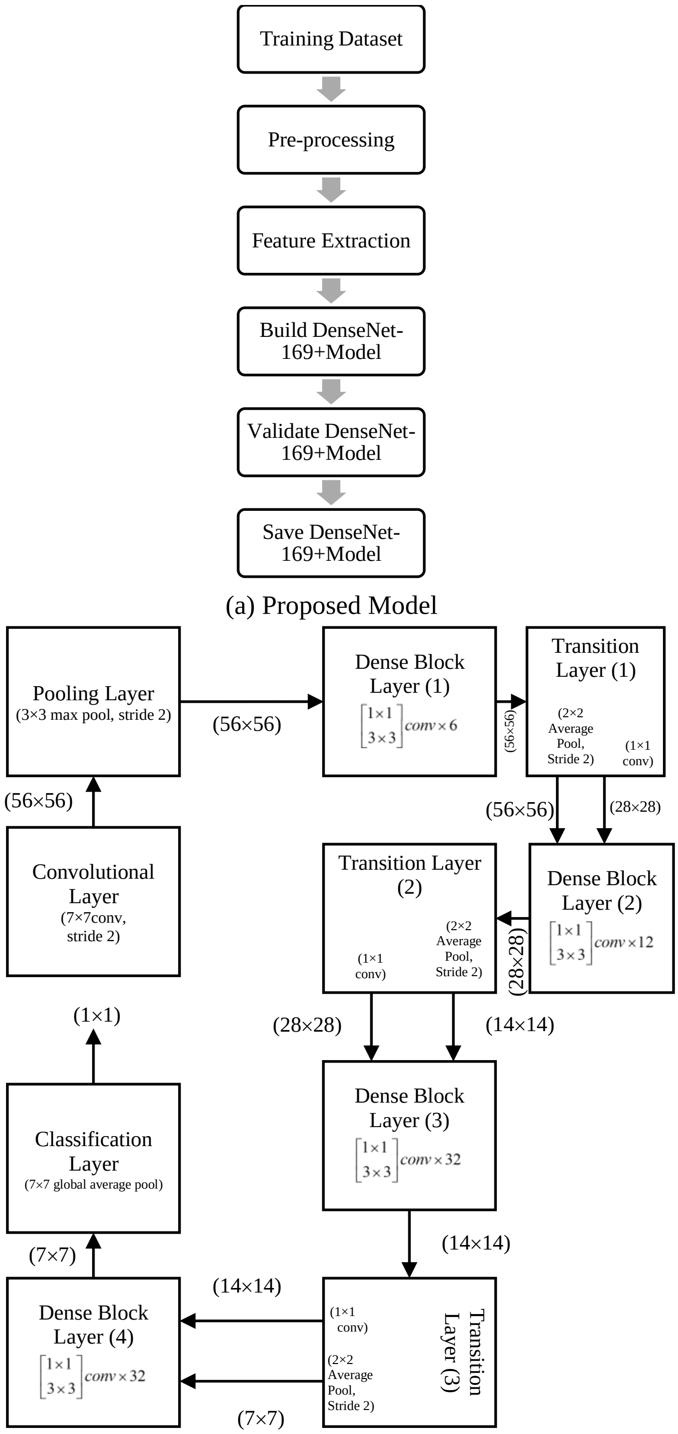
The l^{th} layer output act as an input to the consecutive layer i.e. $(l+1)^{th}$ layer is connected through a traditional convolutional feeding network, which results in transition on a layer:

$$x^l = H^l(x^{l-1}). \tag{1}$$

ResNets further adds a skip connection using a following identity function to bypass the operations of non-linear transformations:

$$x^l = H^l(x^{l-1}) + x^{l-1}. \tag{2}$$

ResNets have the advantage that the gradient can directly pass from conventional layers to previous layers via identity function. The output of Hl however hinders the data flow in the network.



(b) Architecture

Fig.2. Proposed Architecture

3.5 DENSE CONNECTIVITY

The study proposes a distinct connectivity pattern to further improve the flow of data between the layers i.e. from any layer and to improve the dense learning, the study introduce direct connections to all the following layers. The Fig.2 shows the layout schematically of the DenseNet. The l^{th} layer therefore receives all previous layers' feature maps, $x_0, x_1, \ldots, x^{l-1}$, like input:

$$x_l = H^l(|x_0, x_1, \ldots, x^{l-1}|) \tag{3}$$

where, $[x_0, x_1,\ldots,x^{l-1}]$ - concatenation of feature-maps at 0,...,l-1.

The study calls this network architecture the Dense Convolutional Network because of its dense connectivity (DenseNet). The study concatenates several $H^l(\cdot)$ inputs into Eq.(3) for easy implementation in a tensor.

3.6 COMPOSITE FUNCTION

The study defines $H^l(\cdot)$ as a three-fold composing function that includes batch normalization, rectified linear unit and 3×3 Conv.

3.7 POOLING LAYERS

The feature map size changes the concatenation in Eq.(3), which are not considered viable. However, the downsampling layers that change the feature maps size that acts as an essential segment in the dense networks. The study divides the network, where the layers contain densely connected blocks to facilitate the process of down-sampling in the architecture. The study refer to block layers as transitional layers that converge and pool. The transitional layers used for the experiments include a standardisation layer for batch and a convolutional layer of 1×1, followed by a mean pooling layer of 2×2.

3.8 GROWTH RATE

If each Hl function tends to provide k feature maps, where DenseNet-169+ follows lth layer with k0 +k×(l−1) feature-maps with k0 channels in its input layer. The hyperparameter k is called the network growth rate. The study shows a reduced growth rate is enough to achieve the most advanced data sets on which the study is tested.

3.9 BOTTLENECK LAYERS

Although the output characteristics of each layer are k only, typically there are many more entries. It is observed that before each three to three convolutions, the 1×1 convolution could be introduced as a bottleneck layer to reduce the number and thus increase the computational efficiency of inputs.

3.10 COMPRESSION

The study reduces the number of functional maps on transition layers in order to further enhance model compactness. When a dense block contains m function-maps, the study generates output feature maps, where 0 the current value is referred to as the compression factor, using the next transition layer. When $\theta = 1$, there are no changes in the number of feature maps throughout the transition layers. DenseNet-169+ is referred to as 1 in the experiment, the study set a value of $\theta = 0.5$. The study refers to the model as DenseNet-169+ when both the bottleneck and transition layers 1 are used.

4. IMPLEMENTATION DETAILS

The DenseNet is composed of four different dense blocks, each having equal layers, on all datasets with the exception of ImageNet. A convolution of 16 output channels on the image input will take place prior its entry to first block. Each input side is then zero-padded using a single pixel to maintain the size of functional map with a kernel size of 3×3. The transitional layers between two contiguous blocks are 1×1 convolution and an average of 2×2 poolings. A global average grouping takes place at the last dense block, and a softmax classifier is attached. The size of the feature-map is 32×32, 16×16 and 8×8 respectively in the three thick blocks.

The study uses a DenseNet-169+ structure that consists of 4 dense blocks in 224×224 image in the ImageNet experiments. The convolution layer is a 2k convolution size of 7×7 with layer 2; the other layers have a number of characteristics.

5. RESULTS

The entire simulation is conducted on 8x NVIDIA V100 GPUs under a programming language named Python (3.6.6) with Tensorflow (1.9.0) library of functions considered for the purpose of learning. The computing engine used for the proposed method includes following specification that consists is of a CPU: Intel Core i5-3320 M 2.6 GHz with 16 GB RAM. A high-end specification is preferred in the study since the training of classifier is directly linked with the computing time and the computer took 120 minutes for 90 learning sessions. Nearly 80% of the data is used for training and 20% of the data is used for testing purposes.

5.1 DATASET

This DenseNet-169+ is trained on an LUCAS 2018 dataset (https://esdac.jrc.ec.europa.eu/projects/lucas) [25].

In the case of approaches related to the soil classification, some existing approaches are considered for evaluation. This section discusses the evaluation of the methods the researchers have proposed and used in recent years. Evaluation metrics can be used at two levels, i.e. training and testing, in the case of data classification problems. During the training phase, the classification process is used to optimise the predictions of consecutive iterations, and in the test phase, the efficiency of the classification technique is estimated when data are not observed. The best results can be assessed at classification by using the confusion matrix shown in the Table.2 when problems with multiclass soil classification are identified.

Table.2. Confusion Matrix

Parameters	Active Positive Class	Active Negative Class
Predicted Positive Class	TP	FN
Predicted Negative Class	FP	TN

where, Columns defines the actual class, and Rows defines the predicted class. TP – number of negative samples from the input database, where it is correctly classified, TN – number of positive samples from the input database, where it is correctly classified, FP – number of positive samples from the input database, where it is incorrectly classified, and FN – number of negative samples from the input database, where it is incorrectly classified.

Precision (P) is defined as the total positive patterns of the soil that the DenseNet-169+ classifier predicted over entire estimated positive class patterns.

$$P = \frac{tp}{tp + fp} \tag{4}$$

Recall (R) is the defined as the estimation of the ratio of total positive patterns of soil and the correctly classified patterns of the soil.

$$R = \frac{tp}{tp + tn} \tag{5}$$

Accuracy (A) is the ratio of accurate predictions of samples taken for evaluation.

$$A = \frac{tp + tn}{tp + tn + fp + fn} \tag{6}$$

F1-measure is defined the harmonic mean between the recall and precision values.

$$F1 - Measure = \frac{2 * P * R}{P + R} \tag{7}$$

A Mean Square Error (MSE) metric at the training stage can be calculated as a difference between estimates and predicted solutions. To achieve better training performance, the value of MSE must also be low.

$$MSE = \frac{1}{b}\sum_{i=1}^{n}\left(P_i - A_i\right)^2 \tag{8}$$

where, n - Total Samples, P_i - Predicted Sample i and A_i - desired value of sample i.

The Fig.3 shows the results of precision, where the proposed DenseNet-169+Kriging interpolation technique obtains improved rate of precision than other methods. The performance of precision increased from 48% to 69%.

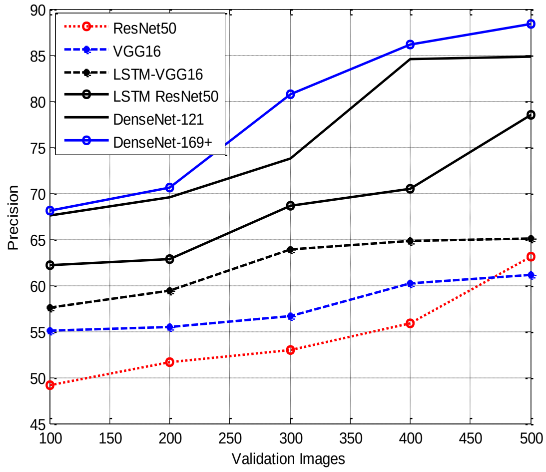


Fig.3. Precision

The Fig.4 shows the results of recall, where the proposed DenseNet-169+Kriging interpolation technique obtains improved rate of precision than other methods. The performance of recall increased from 58% to 80%.

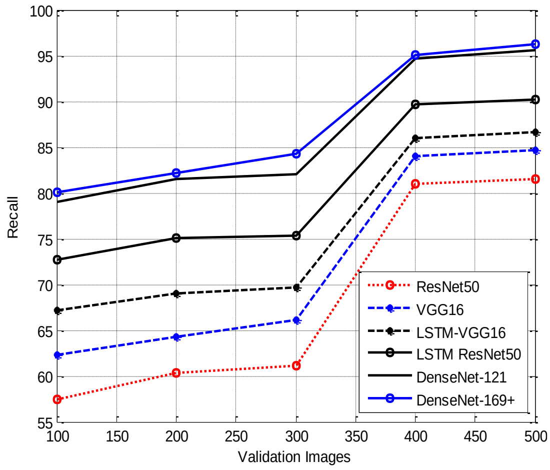


Fig.4. Recall

The Fig.5 shows the results of F-measure, where the proposed DenseNet-169+Kriging interpolation technique obtains improved rate of precision than other methods. The performance of F-measure increased from 28% to 62%.

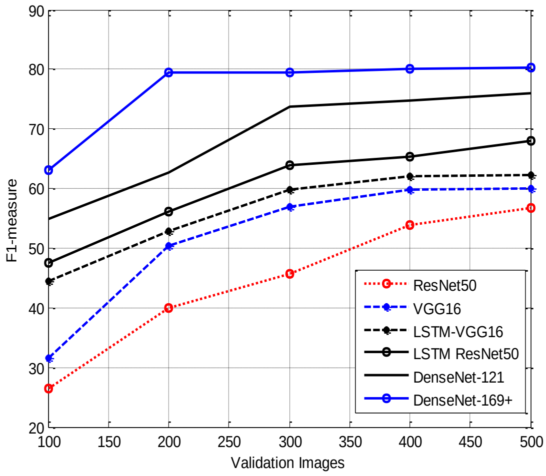


Fig.5. F-measure

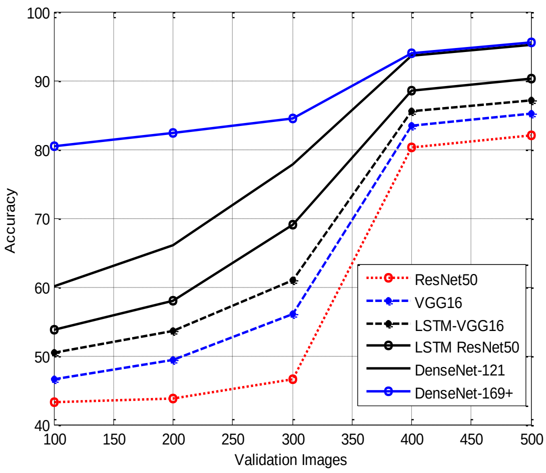


Fig.6. Accuracy

The Fig.6 shows the results of accuracy, where the proposed DenseNet-169+Kriging interpolation technique obtains improved rate of precision than other methods. The performance of Accuracy increased from 43% to 81%.

The Fig.7 shows the results of MSE, where the proposed DenseNet-169+Kriging interpolation technique obtains improved rate of MSE than other methods. The performance of MSE decreased from 57% to 38%.

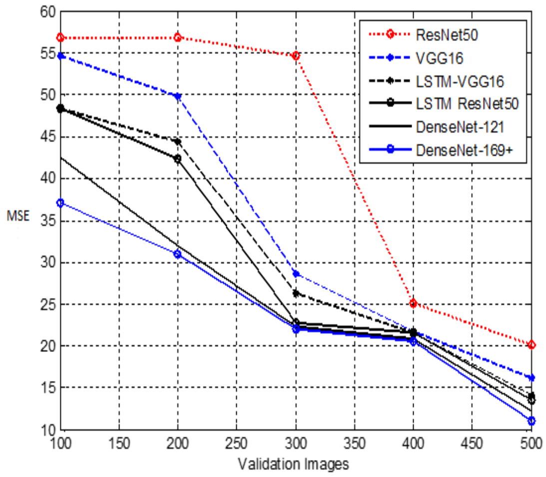


Fig.7. MSE

6. DISCUSSIONS

This research work compares the DenseNet-169+ model with other models such as Resnet50, VGG16, LSTM-VGG16, LSTM-ResNet50, DenseNet-121 in terms of classification accuracy parameters like precision, F1-measure, Recall, Accuracy and MSE for the classification soil images. In this experiment soil images are given as input then convolution layer used for feature detection process. After that, pooling layer shapes the image. Then build the DenseNet-169+ model for evaluating the performance of the classification accuracy. Based on the experiment results DenseNet-169+Kriging interpolation technique gives more accuracy with lower error rate compared to other models. Increasing the number of sessions for learning will improve the overall accuracy level to a certain extent. The study was carried out 70 times to balance the time and the total number of tests.

6.1 LIMITATIONS

However, the DenseNet-169+models offers few limitations, such as the need for large datasets, large computational power and large memory levels. In this experiment only taken 500 images as an input data. In case to increase the dataset size, this model requires higher configuration system otherwise it takes more execution time. Only few metrics are used to assess the accuracy of classification.

7. CONCLUSION AND FUTURE WORK

In this paper, DenseNet-169+ assess the properties of soil via the image classification. The DenseNet-169+ studies the variability index of the soil using Kriging interpolation technique. The results of simulation show an improved accuracy rate, increased precision, sensitivity and f-measure, and a reduced MSE than other models. In contrast, soil classifying approaches based on proposed deep learning reduce the spatial model dependencies and increases the end-to-end learning. In order to overcome the limitations of DenseNet-169+ model, a hybrid approach could be superior. Certain challenges associated with the classification of soil images in the future are given below: There is a need for larger soil image datasets, since in many images, deep-learning models are very good. The soil types vary from one region to another. It is necessary to keep in mind that the storage, cost and time should be reduced, depending on the target user, when involving deep neural networks. Selection of optimal features are considered essential since these features may fulfil various goals. It would also be very beneficial to consider colour as an important feature of the soil.

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