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Research Article

Genetic-Based Neural Network for Enhanced Soil Texture Analysis: Integrating Soil Sensor Data for Optimized Agricultural Management

Jayalakshmi Nagalapuram[1]*, S. Samundeeswari[2]

[1] Research Scholar, Department of Computer Science and Engineering, PRIST University, Thanjavur, India.
* **Corresponding Author Email:** jayanaga1984@gmail.com- **ORCID:** 0009-0000-31371398

[2] Principal, Vandayar Engineering College, Thanjavur, India;
Email: samundeeswari172@gmail.com- **ORCID:** 0009-0007-0646-6994

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Abstract:

Soil texture analysis is vital in agricultural management due to its influence on crop growth and yield. Defined by the proportions of clay, sand, and silt particles, soil texture affects properties like aeration, water-holding capacity, and nutrient retention, all crucial for plant development. The OBJECTIVES: This study aims to design a Genetic-Based Neural Network (GBNN) for accurate soil texture analysis, particularly for soils with similar structures but different compositions. It also aims to collect environmental impact data through soil sensors to enhance the understanding of soil texture.
METHODS: The methodology involves developing a GBNN, leveraging genetic algorithms to group homogeneous particles, thus improving texture classification. This approach addresses the shortcomings of previous deep learning models. Additionally, soil sensor data will be collected to study environmental factors affecting soil texture.
RESULTS: The GBNN showed improved accuracy in texture classification compared to previous models. Genetic algorithms effectively grouped similar particles, and soil sensor data provided insights into environmental impacts on soil texture.
CONCLUSION: The GBNN for soil texture analysis overcame previous models' challenges, improving classification accuracy. The integration of soil sensor data provided valuable environmental insights, aiding farmers in optimizing crop selection, fertilizer application, and soil management for better yields and sustainability.

1. Introduction

Soil texture analysis is a critical component of agricultural management because it provides valuable information about the physical properties of soil that directly impact crop growth and yield [1-6]. Understanding soil texture can help farmers optimize their farming practices and maximize their crop yields while minimizing the negative impacts on the environment. Soil texture analysis is an important task in agriculture and environmental science. It entails figuring out the ratios of clay, sand, and silt grains in a sample of soil, which might have an impact on the soil's physical characteritics including porosity, nutrient retention, and water holding capacity. Traditionally, soil texture analysis has been performed using time-consuming and labor-intensive methods, such as sieving and sedimentation [7]. However, recent advances in computer vision, particularly Convolutional Neural Networks (CNNs), offer a promising solution to automate soil texture analysis (figure 1). Using CNNs for soil texture analysis can offer several benefits (figure 2), such as:

a. Speed and accuracy: CNNs can process large amounts of data quickly and accurately, making them well-suited for analyzing large soil datasets.

b. Automation: CNNs may computerise the examination of soil texture, eliminating the requirement for manual labour and lowering the possibility of human mistake.

c. Objectivity: CNNs provide an objective method for soil texture analysis, eliminating subjective interpretation of results that can arise from manual methods.

d. Scalability: CNNs can be easily scaled to handle larger datasets or more complex analyses, allowing for more detailed and precise soil texture characterization. Overall, the use of CNNs for soil texture analysis can help improve our understanding of soil properties and their impact on agricultural and environmental systems, which can have important implications for sustainable land use management and resource conservation [8]. Soil texture analysis involves determining the proportions of different-sized mineral particles in a soil sample, such as sand, silt, and clay. Convolutional neural networks (CNNs) are a type of machine learning model that can be trained to automatically identify patterns in images, which makes them a suitable approach for analyzing soil texture. To perform soil texture analysis using CNNs, model would need a dataset of labeled soil texture images. The images could be acquired using sensors and images captured from HD camera. The labels would indicate the proportions of sand, silt, and clay in each image. Now the model can train a CNN to classify soil texture images based on their particle size distribution [9-11]. The CNN would learn to identify patterns in the images that correspond to different soil textures. After training, model could use the CNN to classify new soil texture images and obtain estimates of the proportions of sand, silt, and clay in each sample. It's worth noting that training a CNN for soil texture analysis would require a significant amount of labeled data, and it may be challenging to obtain such data [9]. Additionally, the accuracy of the CNN's predictions would depend on the quality of the soil texture images and the variability of soil textures within the dataset.

1.1. Sensors required for analyzing the soil texture

There are several types of sensors that can be used for analyzing soil texture. Some of the commonly used sensors are:

a. Soil moisture sensors: These sensors measure the amount of moisture in the soil, which can help determine the soil texture. Soil with a higher clay content will typically retain more moisture than soil with a higher sand content.
b. Electrical conductivity sensors: These sensors measure the electrical conductivity of the soil, which can be correlated with the soil texture. Soil with a higher clay content tends to have a higher electrical conductivity than soil with a higher sand content.
c. Laser diffraction sensors: These sensors use laser light to measure the particle size distribution of soil samples, which can be used to determine the soil texture. This method is non-destructive and can provide highly accurate results.
d. X-ray fluorescence (XRF) sensors: These sensors use X-rays to measure the elemental composition of soil samples, which can help determine the soil texture. XRF can provide highly accurate results but requires specialized equipment and expertise.
e. Visible/near-infrared (VNIR) spectroscopy sensors: These sensors use light in the visible and near-infrared ranges to measure the reflectance properties of soil samples, which can be used to determine the soil texture. VNIR is a non-destructive and cost-effective method but may require calibration against reference samples.

2. Literature Survey:

Zhuan Zhao et al. [1] Soil impacts crop output and quality by determining the water infiltration level, crop nutrient absorption, and germination. Identifying different soil textures is very difficult using photos, so the author has chosen DLAC, CNN, and RF to identify the soil quality. The implementation was performed through deep learning and machine learning. Deep learning can handle image segmentation with accuracy, and machine learning has good performance. The images are classified into three features: particle, colour, and texture. Now all extracted features are classified accordingly; the particle is derived in binary format, and those are valued in the threshold. In the texture feature, the images are derived in grayscale format, and those are derived in two-phase binary patterns and features of haralick. Finally, the colour feature has two phases: grayscale and HSV. Where HSV is derived in patterns and grey is derived in Hu moments. All these features are combined to form a global feature and are connected to some target values that have been identified. The proposed model, train the model, predict the values according to the three phases, and finally identify the soil types. Soil texture is an important factor in assessing soil health. Manually categorising soil texture 1 and 2 is costly, time-intensive, and requires trained professionals, who are typically in short supply.

a. Soil Moisture b. Electrical Conductivity c. Diffraction d. XFR Sensor

Figure 1: *Sensors for Soil Texture Analysis*

Pallavi Srivastava et al. [2] focused on the soil to identify the quality and distinguish the high performance through image segmentation. For this, DNN and CNN were used for their high performance in filtering the layers. The data collected from five different crops was considered from different places in India. The images need to be acquired for the different images where they are derived in a different format for more classification. The derived images are texture determined, and CNN is used for filtering the images and deriving the essential parts. Here, the USDA is used for differentiating the samples. Now the images have to be segmented, and after pre-processing, the hydrometer is used for the soil texture based on the USDA triangle. For this, the graph is derived based on the threshold values. Later, CNN is applied for more filtering of the images for accurate performance and efficiency. Hence, accuracy was considered based on train and test data with three transfer learning parameters.

The automated analysis of digitised soil section pictures shows soil structural features and generates preliminary assessments of bioecological relevance, such as soil richness and shifts in ecosystems on land. Anastasia Sofou et al. [3] have proposed a method using computer vision where the machines do the work of image segmentation of the plant. Initially, the data needs to be segmented in three different stages: pre-processing, extraction of features, and the proposed method for morphological operations. It was generated in three phases, where the working and the segmentation were processed. The outcome data is derived based on the texture, which considers five phases related to its forms. For this, the two dimensions are used for identifying the AM-FM frequency. From there, the unique values are derived using the 2-D energy operators. Finally, the CSS is used for checking the level of the soil with respect to threshold values, which are defined accordingly. To maximise crop output while utilising limited land resources, it is critical to determine and select the suitable kind of soil since various crops require different soil types. At present, there are two methods available for determining soil type: chemistry and image analysis. Machbah Uddin et al. [4] Based on the two phases, the initial one is too tough for working, so the author has to work on the second phase, where the performance will be easily retrieved because of image segmentation. In the initial phase, the three models are derived in multiple channels; the initial channel used the proposed method called Q-HOG and the feature extraction method called Haralick. The remaining colours are connected to different features, and all these features are connected to global features, where the selection has to take place in the next stage. For the selection features, the input values are target soil levels. Now the selected features are described by decreasing the size of the feature. The four machine learning methods are used to predict the most efficient soil. The model is trained and tested using some images, and finally, the results are obtained. Soil texture is a key aspect of agricultural output, and its accurate forecast is critical for ensuring the effective administration and utilisation of water resources. K. Anandan et al. [5] have focused on different soil textures where deep learning is used for the prediction of soils. Among many approaches, CNN has high performance in determining and detecting values. This method identifies the six different soil properties, and each image is segmented based on the filters in the CNN. Any neural network has three layers, of which two are fixed and the hidden layer works based on the filtering ranges. Hyperspectral information is a soil analysis approach that records the colour and spectral features of the soil. Organic carbon, cation exchange capacity, clay, sand, pH, and nitrogen are all soil characteristics. The next sections describe how a CNN approach was used for training the location data mapped to soil texture. The goal is to aid in different hydrologic processes as well as precision agriculture. The paragraphs also discuss some of the obstacles and limitations of utilising hyperspectral data to forecast soil features. In table 1 some previous works have been listed.

Table 1. *Previous works and their merits and demerits.*

Author	Algorithm	Merits	Demerits	Accuracy
Zhuan Zhao	DLAC-CNN-RF	CNN has the best features for deriving image segmentation	While the features are extracted the identification takes more time.	99%
Pallavi Srivastava et al	CNN, DNN	Using USDA has a high-performance range.	The time complexity is high when the image is pre-processed.	98%
Anastasia Sofou et al	AM-FM	This phenomenon is derived from high images.	If the dataset size is high the performance is tuff.	85%
Machbah Uddin et al	Haralick, Q-HOG, ML	The Q-HOG is a hybrid method where the features are found efficiently.	No need of using three different features at a time.	90.8%
K Anandan et al	CNN	The proposed method has used fewer layers and easy retrievals.	Only works on particular soils.	96%

3. Proposed methodology:

The proposed model uses the StyleGAN for soil texture analysis to design an unconventional approach that can potentially generate synthetic soil texture images that can aid in soil texture analysis. After training, the style GAN would be able to generate new synthetic soil texture images that are similar in style and composition to the training set. These synthetic images could be used to augment the original dataset, increasing its size and diversity. Once model have a synthetic dataset, it can train an autoencoder to reconstruct the soil texture images. The autoencoder would learn to encode the input images into a lower-dimensional representation, also known as a latent space, and then decode this representation back into an output image. One potential advantage of using autoencoders for soil texture analysis is that they can learn a more compact and meaningful representation of the soil texture images compared to other methods. Whale optimization is a type of metaheuristic optimization algorithm that is inspired by the social behavior of humpback whales. To use whale optimization over CNN for soil texture analysis, you would first need to define the objective function that you want to optimize. In the case of training a CNN, the objective function could be the training loss, which is the measure of how well the model fits the training data.

3.1. Style GAN:

The StyleGAN is an evolution of the continuous growing GAN, which is a method for training a discriminator and producer models that can synthesise very big, high-quality pictures by gradually expanding them from tiny to huge images during training. Without affecting other levels, it transforms the input of each level separately and analyses the visual qualities that are evident in that level, from common aspects like stance and facial shape to subtle nuances. The styleGAN is a particular sort of generative adversarial network. With help from the style send literature and, in particular, adaptive instance normalisation, it provides a different generator development for generative adversarial networks. This style vector's benefit is that it gives you control over how the resulting picture behaves. Through the addition of turbulence at a particular location in the generator model, stochastic variation is proposed.

4. Convolution Auto Encoder:

Convolutional autoencoders are a particular kind of unsupervised learning model that have been trained to recreate the input image in the output layer. An encoder, that is a ConvNet that creates a low-dimensional model of the picture, processes an image that is sent through it. The decoder uses this compressed picture to rebuild the original image using another sample ConvNet.

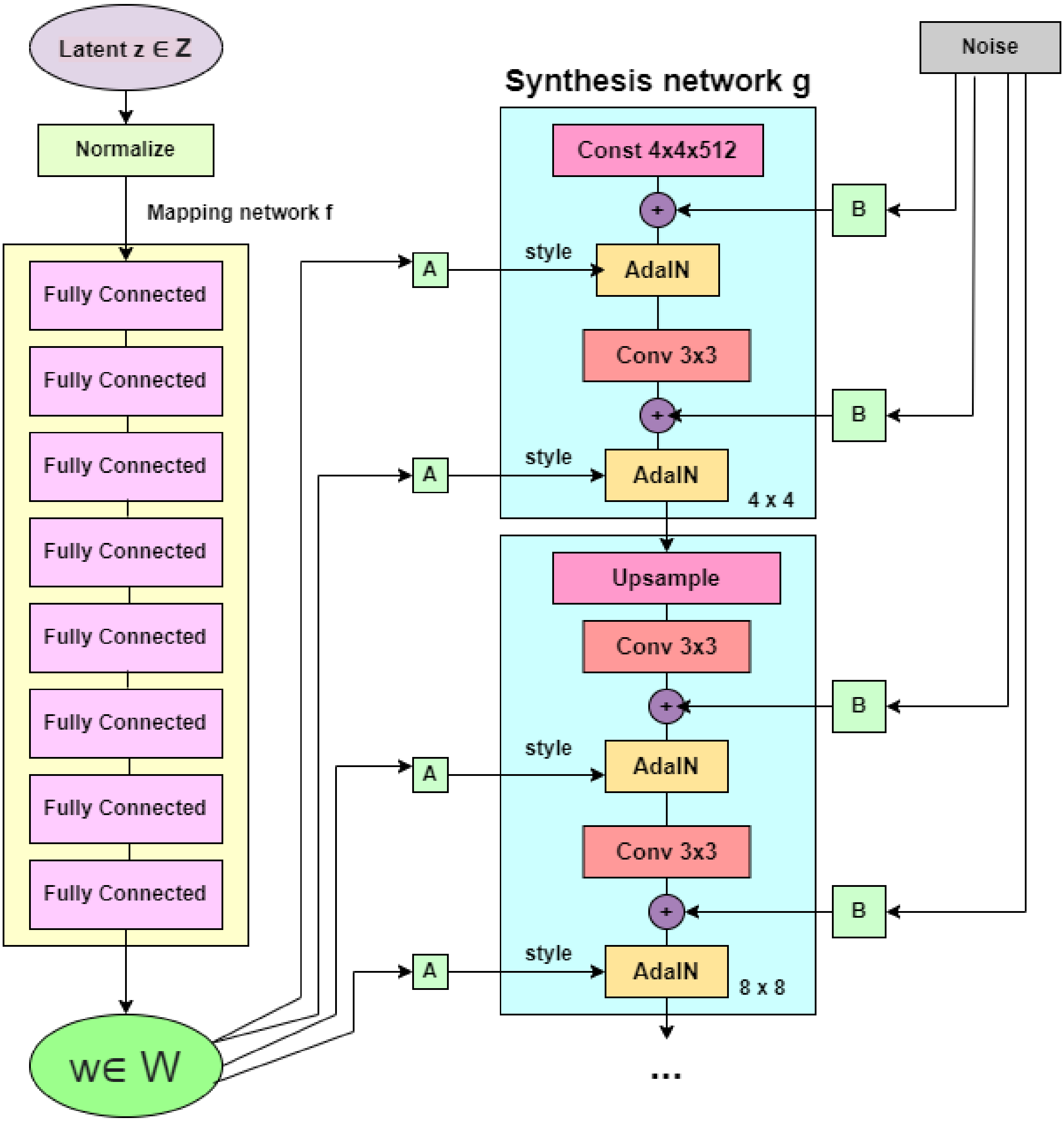

Figure 2: *Working of Style GAN in Synthetic Images Generation*

Data is compressed using an encoder, and the original picture is reproduced using a decoder. Autoencoders can therefore be employed for data compression. As opposed to predetermined compression algorithms like JPEG, MP3, and the like, compression reasoning is data-specific, implying it is learned from data. The primary distinction between the traditional analysis of CNN and CAE is the former's end-to-end training in the acquisition of filters and the combining of features with the goal of categorising input. The latter are merely taught filters that can extract information from the input and be used to rebuild it.

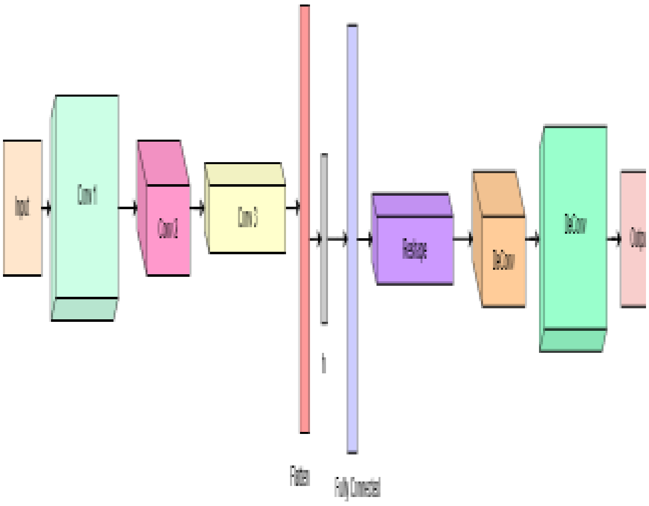

Figure 3: *Blocks of Auto Encoder in Soil Particle Extraction Process*

4. 1. Whale Optimization:

WOA was particularly influenced by the social interactions and bubble-net foraging of humpback whales in the ocean. Starting with a collection of random solutions, the WOA algorithm runs. Each time they iterate, search agents adjust their placements in relation to either the best result thus far or a randomly selected search agent. The a parameter is decreased from 2 to 0 to aid in exploration and exploitation. Without requiring structural reformation, WOA is a suitable technique for tackling many restricted or unconstrained optimisation issues for practical applications. Whales use a technique known as the "bubble net attacking method" to attack their prey by shooting bubbles towards the water's surface while they move in a diminishing spiral arc around it. The algorithm refers to it as the spiral update position and the diminishing encircling mechanism. The goal is to carefully approach the target by spiralling in a nine-pointed pattern around it. The algorithm's simplicity—it simply has two internal configurable parameters—is its biggest benefit.

Pseudocode

Input: Input data, population size and Number of max_iter etc

Output: Best parameters for CNN

Begin

1. Initialize the population of whales with random weights and biases for the CNN.

2. Evaluate the fitness of each whale in the population using the CNN's performance on the training set. The fitness function can be the loss function used for training, such as cross-entropy loss or mean squared error.

3. Repeat until convergence:

a. Sort the whales by fitness in descending order.

b. Select the top-performing whales as parents for the next generation.

c. Generate new offspring by applying crossover and mutation operators to the parents' weights and biases.

d. Evaluate the fitness of the new offspring using the CNN's performance on the training set.

e. Replace the least fit whales in the population with the new offspring.

f. Update the position of the whales using the equation:

new_position = position + A * distance_to_target * exp(-C * t) * rand() + A * rand() * (best_position - position)

where A is the amplitude of the search, C is a constant, t is the current iteration, and rand() generates a random number between 0 and 1. The distance_to_target is the Euclidean distance between the whale's current position and the target solution (i.e., the best-performing whale).

4. Return the best-performing whale as the solution to the optimization problem, which corresponds to the optimized weights and biases for the CNN. Use the optimized CNN to perform image texture analysis, such as classification or segmentation, on new unseen images.

4.2 Loss Function:

In whale optimization, the objective function is the function that model want to optimize. In the case of training a CNN for soil texture analysis, the objective function could be the training loss. The training loss is a measure of how well the CNN fits the training data. During the training process, the CNN attempts to minimize the training loss by adjusting its weights and biases. The lower the training loss, the better the CNN is at recognizing soil texture. To use whale optimization to optimize the CNN's hyperparameters, you would need to define the training loss as the objective function. The whale optimization algorithm would then search the hyperparameter space to find the set of hyperparameters that minimizes the training loss. The loss function determines the discrepancy between the algorithm's desired and present outputs (figure 4). It's a method for determining how well your programme replicates the data. It may be split into two groups. The first is for grouping (discrete values, 0, 1, 2, etc.), while the second is for regression (consistent values). Simply expressed, a loss function shows how inaccurately the model predicts the link between x and y. Loss functions are a way to measure how effectively your model is able to predict the intended outcome. Despite the fact that loss functions may not be immediately applicable to human beings or straightforward to comprehend, they can nonetheless give information about the performance of our model. In this case, metrics are useful.

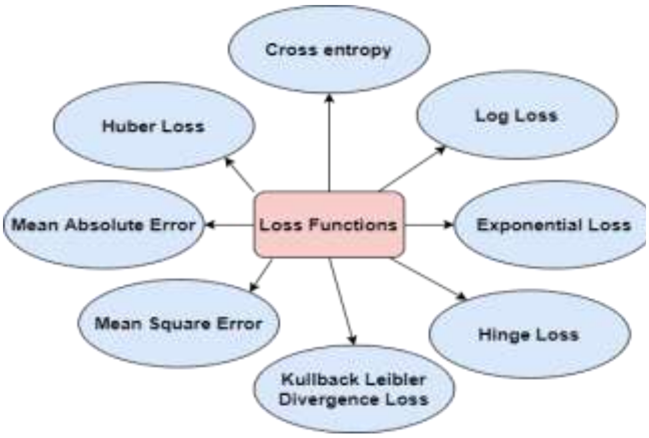

Figure 4: *Classification of Loss Function*

There are several types of loss functions that can be used as the objective function for whale optimization, depending on the specific task and dataset (figure 3). For soil texture analysis, common loss functions include mean squared error (MSE), categorical cross-entropy, and binary cross-entropy.

5. Results & Discussion

The figure 5 demonstrates the different layers present in the auto-encoder model of convolutional neural networks. The architecture has 3 different layers. The initial layer is the input layer to accept images as input to convolution, and the image

```
Model: "autoencoder"
_________________________________________________________________
Layer (type)                Output Shape              Param #
=================================================================
img (InputLayer)            [(None, 28, 28, 1)]       0
_________________________________________________________________
flatten_1 (Flatten)         (None, 784)               0
_________________________________________________________________
dense_3 (Dense)             (None, 128)               100480
_________________________________________________________________
dense_4 (Dense)             (None, 128)               16512
_________________________________________________________________
dense_5 (Dense)             (None, 784)               101136
_________________________________________________________________
reshape_1 (Reshape)         (None, 28, 28, 1)         0
=================================================================
Total params: 218,128
Trainable params: 218,128
Non-trainable params: 0
```

Figure 5: *Summary of Auto Encoder*

processing starts there. The following layer is the flattening layer which minimizes the dimension of the output to a long and single layer of a continuous vector. There are 3 dense layers in the model. The image classification is done in this layer and uses the output values of its preceding layer, which is flattening. Without altering the data, the Reshape layer may be used to adjust the input's dimensions.

```
[0.         1.2377704  0.14265895 2.0361598  0.         0.5866665
 0.         0.         0.47920284 0.5132057  0.         0.86886317
 0.69851273 1.0580643  0.68369657 0.68564606 0.04866482 0.41543257
 1.711677   0.7418289  0.16621575 0.77250403 0.88879985 0.
 0.46652475 0.         1.0602275  0.5153241  0.80959153 0.
 1.2147571  0.20485583 0.31451473 1.0702908  1.2018458  0.7584589
 0.42187098 0.20959589 0.67256093 0.         0.29393718 1.6756594
 0.9369522  0.4024997  0.5539635  0.54783386 1.5283211  0.5267148
 0.79602736 0.5574524  0.71925926 0.75930613 0.40550807 0.558127
 0.3994823  1.2324069  1.6244261  0.48817268 1.1560764  0.80559117
 0.04895455 0.24240041 0.2885805  0.15965319 1.8077133  0.
 0.         0.         0.8552021  0.6593257  0.71643996 0.8933082
```

Figure 6: *Feature Extraction from Soil Texture Images*

Figure 6 represents the vector representation that involves in converting an image of soil texture into a set of numerical features that can be used for machine learning analysis. In this approach, each image is represented as a vector of features, where each element of the vector corresponds to a specific feature of the image. Figure 7 represents the accuracy of the VGG algorithm at each epoch. The entire number of cycles necessary to train the algorithm concurrently utilising every bit of training information is known as an epoch. Cycles are used to measure it. Another way to establish an epoch is to count how many times a training dataset circles an algorithm. It can be observed that by the increase of the count of epochs, the accuracy of the model also increased.

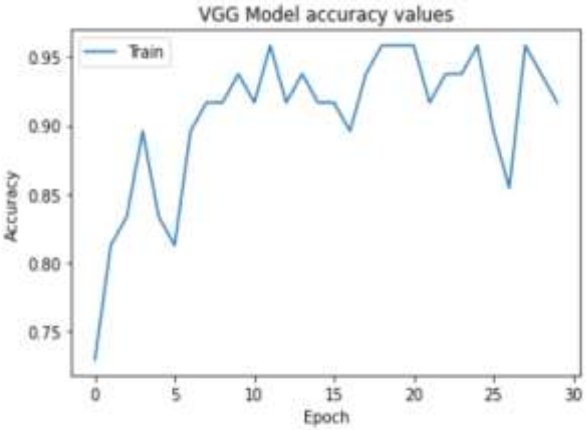

Figure 7: *Accuracy Analysis using VGG Model*

Accuracy is the measure of the efficiency of the system. At the zeroth epoch, the accuracy started at around 71% and rose to 95% by the 27th epoch. It indicates that the model's training is going well and the model is ready to test. The values of loss function decrease gradually as the model is trained.

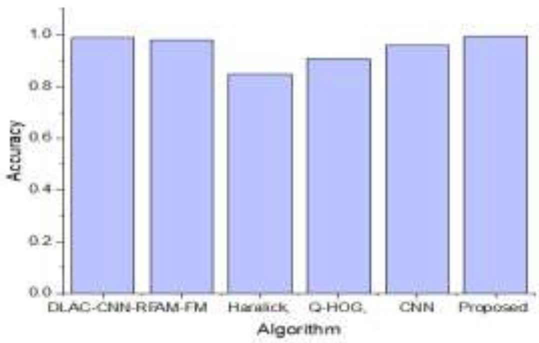

Figure 8: *Evaluation Analysis*

The existing methods are compared with the proposed model in the figure 8. It shows that the models DLAC-CNN-RF and CNN have approximately the efficiency or the values of accuracy are so near to the proposed model. Even though the proposed model is able is conclude in less time when compared with theirs. The proposed model is cable of working effortlessly when the dataset is of high dimensions and size. It can be seen that other previously proposed methods like Harlic, Q-hog, AM-FM, etc have scored results that are less accurate. There is a need to re-study those and do the needed updations. The proposed model has achieved noteworthy outcomes.

6. Conclusion:

Soil texture is important in nutrient management because it impacts nutrient absorption. For instance, finer-textured soils frequently have a better ability to preserve soil nutrients. There are manual techniques accessible in general for identifying soil properties and classifying soils, but professionals are needed for this. As a consequence, various specialists provide different results. Methods for extracting characteristics are being utilized for higher-level research. The proposed model is composed of different methods they are processed using Style GAN and then the produced images are sent for feature extraction and classification through convolution auto-encoders. The images are sent for whale optimization and are evaluated using the binary loss function. There are other ways to extract characteristics, however, the methods used for the soil photos above are the best. The images are taken from the soil texture dataset. The proposed method has proved its efficiency with obtained accuracy.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

- **Acknowledgement:** The authors declare that they have nobody or no-company to acknowledge.

- **Author contributions:** The authors declare that they have equal right on this paper.

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- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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