Mapping The Open Pit Mine Areas Using Feedforward Neural Network Classification (FNN)

A.V. Adlin grace [1], C Puspalatha [2]
[1, 2] Dept of CSE
[1, 2] Arunachala College Of Engineering

Abstract- *Earth's resources are strained; the need for sustainable development is growing. Among them, coal resources are continuously mined as an important energy source for industrial development, and the number of closed mines is gradually increasing. This project proposes a mapping the open pit mine areas using feed forward neural network. Input image sent for preprocessing. For preprocessing used wiener filter. It is used to filter out the noise from the corrupted signal to provide an estimate of the underlying signal of interest. Then the preprocessed image is move for feature extraction. Feature extraction helps to reduce the amount of redundant data from the data set. K-means is utilized for segmentation. The segmented is further transfer for classification. Feed forward neural network (FNN) is used in classification. This project is implemented with MATLAB simulation software.*

Keywords- Earth's resources, coal resources, industrial development, forward neural network, MATLAB.

I. INTRODUCTION

Mineral resources are raw materials necessary for social and economic development, which are of great significance to the survival and development of human beings. Currently, there are widespread illegal and unauthorized mining activities globally, which not only disrupts the order of mineral resource development but also causes irreversible damage to the ecological environment. Rapid identification and monitoring of mining areas and illegal mining have become important tasks for natural resource management departments at all levels of government. This article topic is of practical significance as it aligns with the policy demands of various levels of government. In early work, the location of mining areas and information on the extent of mining were obtained through field surveys. This method was time-consuming, labour-intensive, and unsuitable for large-scale, routine inspections. High spatial resolution remote sensing (HRS) images can quickly obtain clear information about the land surface over a large area. At the same time, the continuous improvement of spectral resolution has also provided the possibility for obtaining fine-scale mining area types information for large-scale scenes. Since the 1970s, remote sensing technology has been widely used in land cover detection and land use mapping tasks. According to the different research units, technology can be divided into pixel- and object-based methods. The former takes a single pixel in an HRS image as the research object, constructs shallow features of ground features, and then uses a simple threshold method to classify the targets. In the early research on remote sensing detection of mining areas, spectral index methods edge detection methods and other methods were the most typical representative methods of that period. Although these methods were simple and easy to operate, the detection accuracy was relatively low. Object-based methods study objects composed of multiple related pixels. This method considers the spatial structural characteristics between ground features and can achieve higher detection accuracy than pixel-based methods. However, how to adaptively select a reasonable segmentation scale is still a bottleneck and difficulty of this method. With the development of machine learning, scholars have gradually used various machine learning algorithms to replace thresholding methods for mining features of mining areas, such as decision trees support vector machines and deep belief networks. Although machine learning methods have achieved good results, more powerful algorithms are needed to explore deeper semantic features due to the complexity of land cover and the irregularity of spatial distribution in mining areas.

Open-pit mining, also known as open-cast or open-cut mining and in larger contexts mega-mining is a surface mining technique of extracting rock or minerals from the earth from an open-air pit, sometimes known as a borrow. This form of mining differs from extractive methods that require tunnelling into the earth, such as long wall mining. Open-pit mines are used when deposits of commercially useful ore or rocks are found near the surface. It is applied to ore or rocks found at the surface because the overburden is relatively thin or the material of interest is structurally unsuitable for tunnelling (as would be the case for cinder, sand, and gravel). In contrast, minerals that have been found underground but are difficult to retrieve due to hard rock, can be reached using a form of underground mining.To create an open-pit mine, the miners must determine the information of the ore that is underground. This is done through drilling of probe holes in the ground, then plotting each whole location on a map. The information gained through the holes with provide an idea of the vertical extent of the ore's body. This vertical information is then used to pit tentative locations of the benches that will occur in the mine. It is important to consider the grade and economic value of the ore in the potential pit. Open-pit mines that produce building materials and dimension stone are commonly referred to as quarries. Open-pit mines are typically enlarged until either the mineral resource is exhausted, or an increasing ratio of overburden to ore makes further mining uneconomic. When this occurs, the exhausted mines are sometimes converted to landfills for disposal of solid wastes. However, some form of water control is usually required to keep the mine pit from becoming a lake, if the mine is situated in a climate of considerable precipitation or if any layers of the pit forming the mine border productive aquifers. In Germany and adjacent countries several former open-pit mines have been deliberately converted into artificial lakes, forming areas such as the Lusatian Lake District, the Central German Lake District or the Upper Palatinate Lake District. A particular concern in the formation of these lakes is acid mine drainage.

Heart failure disease (HFD), which has the highest global prevalence, has a multi-factorial pathology. In some cases, cardiac output is reduced due to changes in mechanical properties and altered cardiac electrical activity. A number of neurohormonal regulatory mechanisms are activated in the early stages of HFD. Although these compensatory mechanisms can compensate for the effects of HFD in the short term, they can cause dyspnea on exertion, pulmonary and peripheral edema, heart remodeling, and exacerbate ventricular dysfunction, which can cause permanent changes in preload and after load. Many treatment options are offered to patient with HFD such as life style changes, medications or implantable devices such as a pacemaker or defibrillator. Following up with this population is a major concern, given that hospitalization due to acute HFD decompensation is the leading cause of health care expenditure. According to studies and statistics, heart disease is the most serious problem that people face, particularly HFD. Early detection and diagnosis of cardiac disease, like other diseases, is the first step in treatment and care.

Open-pit mining, also known as open-cast or open-cut mining and in larger contexts mega-mining is a surface mining technique of extracting rock or minerals from the earth from an open-air pit, sometimes known as a borrow. This form of mining differs from extractive methods that require tunnelling into the earth, such as long wall mining. Open-pit mines are used when deposits of commercially useful ore or rocks are found near the surface. It is applied to ore or rocks found at the surface because the overburden is relatively thin or the material of interest is structurally unsuitable for tunnelling (as would be the case for cinder, sand, and gravel). In contrast, minerals that have been found underground but are difficult to retrieve due to hard rock can be reached using a form of underground mining. To create an open-pit mine, the miners must determine the information of the ore that is underground. This is done through drilling of probe holes in the ground, then plotting each whole location on a map. The information gained through the holes with provide an idea of the vertical extent of the ore's body. This vertical information is then used to pit tentative locations of the benches that will occur in the mine. It is important to consider the grade and economic value of the ore in the potential pit. Open-pit mines that produce building materials and dimension stone are commonly referred to as quarries. Open-pit mines are typically enlarged until either the mineral resource is exhausted, or an increasing ratio of overburden to ore makes further mining uneconomic. When this occurs, the exhausted mines are sometimes converted to landfills for disposal of solid wastes. However, some form of water control is usually required to keep the mine pit from becoming a lake, if the mine is situated in a climate of considerable precipitation or if any layers of the pit forming the mine border productive aquifers. In Germany and adjacent countries several former open-pit mines have been deliberately converted into artificial lakes, forming areas such as the Lusatian Lake District, the Central German Lake District or the Upper Palatinate Lake District. A particular concern in the formation of these lakes is acid mine drainage.

Open-cast mines are dug on benches, which describe vertical levels of the hole. The interval of the benches depends on the deposit being mined, the mineral being mined, and the size of the machinery that is being used. Generally, large mine benches are 12 to 15 meters thick. In contrast, many quarries do not use benches, as they are usually shallow. Mining can be conducted on more than one bench at a time, and access to different benches is done with a system of ramps. The width of each bench is determined by the size of the equipment being used, generally 20–40 meters wide. Downward ramps are created to allow mining on a new level to begin. This new level will become progressively wider to form the new pit bottom. Waste rock is stripped when the pit becomes deeper, therefore this angle is a safety precaution to prevent and minimize damage and danger from rock falls. However, this depends on how weathered and eroded the rocks are, and the type of rocks involved. It also depends on the amount of structural weaknesses occur within the rocks, such as a faults, shears, joints or foliations. The walls are stepped. The inclined section of the wall is known as the batter, and the flat part of the step is known as the bench or berm. The steps in the walls help prevent rock falls continuing down the entire face of the wall. In some instances additional ground support is required and rock bolts, cable bolts and shot Crete are used. De-watering bores may be used to relieve water pressure by drilling horizontally into the wall, which is often enough to cause failures in the wall by itself. A haul road is usually situated at the side of the pit, forming a ramp up which trucks can drive, carrying ore and waste rock.

II. LITERATURE SURVEY

The Muli coalfield, a typical alpine mining area on the Qinghai Tibet Plateau (QTP) is proposed in this paper. The results show that: (1) the land use transfer process changed from active to basically stable. During the mining phase, the land use transfers were complex and mainly consisted of the transfers of grassland to production land. The land use transfers during the restoration phase were not obvious. (2) Natural landscape types (e.g., river and grassland) were separated by surface mining. In terms of landscape fragmentation, the patch densities showed an increasing trend, while the patch shape fragmentation index showed first decreased and then increased. Summarized the lessons learned from the mining and restoration processes and provided a reference for addressing the conflict between mineral exploitation and environmental protection in ecologically fragile alpine mining areas. Nevertheless, there was a decrease during the first stage because the original grassland and river were composed of large intact patches with multiple upward extensions, so the patch shapes were complex and irregular.

A Stepwise Framework for Fine-Scale Mining Area is proposed in this paper. The framework consists of two steps. First, a GF-5 spectral index named the Normalized Difference Mining Area Index (NDMAI) is constructed to obtain the rough position of the mining area quickly. Then, the identification network of Mine Types with Transformer (Mitformer) is proposed for accurate type recognition of the candidate mining area regions. The experimental results illustrate that this framework can provide adequate technical support for the dynamic detection of mineral resources. However, this article still has many limitations. For example, due to the difficulty of data acquisition, the selected study areas in this article mainly focus on sand and metal mines, with a relatively small number of types.

In open-pit mines, underground mines blasting are a helpful method for fragmenting rocks. Blasting is particularly used in ground vibration, has major adverse effects on the environment. Bombardment is still regarded as the most popular technique for fracturing rock in open-pit mines and during engineering construction. Rock masses are fractured by the release of explosive energy. Blasting is a useful technique for rocks fragmentation in open-pit mines, underground mines, as well as for civil engineering work. However, the negative impacts of blasting, especially ground vibration, on the surrounding environment are significant. Ground vibration spreads to rocky environment and is characterized by peak particle velocity (PPV). At high PPV intensity, structures can be damaged and cause instability of slope.

The tunnel collapses due to loss of rock integrity, the presence of underground pockets of gases, or ground water. The blast vibration in an open-pit lignite mine was predicted using an artificial neural network by factoring in frequency, charge per delay, distance, and scaled distance. The output parameters are progressively transverse peak, vertical peak, and longitudinal peak particle velocities. Channel attention focuses on what is input, whereas spatial attention focuses on the location of the information, and spatial attention is complementary to channel attention. Channel attention uses global average pooling and global max pooling to obtain the relationship between feature channels to generate channel attention maps, and spatial attention uses average pooling and max pooling along the channel axis to obtain spatial feature attention maps.

The demand for reliable and robust crisis information after catastrophic disasters has substantially grown in the past decades. Earth observation satellites are increasingly used to obtain reliable large-scale crisis information, owed to their ability of being almost independent of the underlying terrain, the possibility of acquiring data over large areas in a short amount of time and their different sensor systems. To provide the required information in a timely manner, international initiatives such as the International Charter “Space and Major Disasters” have been founded, linking space agencies from all over the world and allowing a rapid disaster response by sharing the available satellite resources.

Recent years have witnessed a growing interest in the use of U-Net and its improvement. It is one of the classic semantic segmentation networks with encoder-decoder architecture and is widely used in medical image segmentation. In the series versions of U-Net, U-Net++ has been developed as an improved U-Net by designing an architecture with nested and dense skip connections, and U-Net 3+ has been developed as an improved U-Net++ by taking advantage of full-scale skip connections and deep supervision on full-scale aggregated feature maps. Each network architecture has its own advantages in the use of the encoder and decoder. An efficient and lightweight U-Net (ELU-Net) with deep skip connections was implemented. The deep skip connections include same- and large-scale skip connections from the encoder to fully extract the features of the encoder.

A serious earthquake could trigger thousands of landslides and produce some slopes more sensitive to slide in future. Landslides could threaten human's lives and properties, and thus mapping the post-earthquake landslide susceptibility is very valuable for a rapid response to landslide disasters in terms of relief resource allocation and posterior earthquake reconstruction. Many methods to map landslide susceptibility but seldom considered the spatial structure information of the factors that influence a slide. The performance of this U-net like model was also compared with those of traditional logistic regression and support vector machine models on both the model area and independent testing area with the former being stronger than the two traditional models.

The Estimation of accurate attenuation maps for whole-body positron emission tomography (PET) imaging in simultaneous systems is a challenging problem as it affects the quantitative nature of the modality. Here, it is mainly aimed to improve the accuracy of estimated attenuation maps from Dixon contrast images by training an augmented generative adversarial network in a supervised manner. The workflow consists of the training step and the estimation of map for PET image reconstruction. In the training step, the images were co-registered and augmented for each patient dataset. The normalized images were used to train the generator to predict μ-map. The predicted μ-map and the actual μ-map are then inputted into the discriminator network.

Mining activities are the leading cause of deforestation, land-use changes, and pollution. Land use/cover mapping in Vietnam every five years is not useful to monitor land covers in mining areas, especially in the Central Highland region. It is necessary to equip managers with a better tool to monitor and map land cover using high-resolution images. Therefore, the authors proposed using the U-Net convolutional network for land-cover classification based on multispectral unmanned aerial vehicle (UAV) image in a mining area of Daknong province, Vietnam. Recently, the artificial neural network (ANN) has become a useful tool to deal with complex non-linear regression between input data that has not yet been optimized for ancient remote sensing processing techniques such as unsupervised learning, Random Forest, pixel-based and Support Vector Machine.

The Placer mining is a mineral extraction method in floodplains that involves the removal of earth material to access mineral-laden sediments, a process that can have significant and long-term impacts on aquatic ecosystems. Given the widespread nature of mining, new tools are required to monitor the potential watershed-scale ecological impacts of placer mining. The model was adapted and evaluated a deep learning model – a U-Net convolution neural network, and compared it to a traditional image classification method. There is an increasing interest in the use of remotely sensed data for monitoring mining areas as most available methods and techniques can achieve high land-use/land cover classification as well as improved accuracy in extracting environmental variables.

III. PROPOSED SYSTEM

The management of unstable slope is a fundamental challenge in open-pit mines, mainly aimed at maintaining the safety of mine operations and at reducing perspective economic losses. In this context, an adequate early warning system is a valuable tool to reduce the impact of slope failures on the mine life. Monitoring and forecasting activities represent operational steps, and their efficiency is strongly related to the performance of the techniques employed in the monitoring phase, which influences the goodness of the acquired data and consequently the forecasting results. Common instruments deployed for safety critical monitoring in open-pit mines are extensometers total stations, and GNSS receivers. Lately, after 20 years of experimentations in different field ground based interferometric synthetic aperture radar (GB-InSAR), or slope stability radar as it is most known in the mining industry, stood out as the cutting edge technology for real-time slope failure monitoring aimed at identifying critical displacement thresholds useful for triggering response plans in open-pit mines. Also satellite InSAR techniques are employed in monitoring slope stability as well as other natural phenomena that induce terrain deformation, such as earthquakes volcanic activity ground subsidence and uplift glacier motion. Traditionally, satellite InSAR techniques are mostly used for long-term monitoring, ground deformation mapping, and landslide inventories whereas early warning applications were out of reach, due to limitations in the data acquisition frequency, until recently. During the last 25 years, satellite techniques have seen an increasingly greater diffusion. Thanks to their inherent characteristics, they present several of advantages in the field of monitoring activities, such as they are able to observe the investigated scenario in any lighting and weather condition, producing displacement maps at a large scale, with mill metric accuracy and without physical access to the observed area. Among the other characteristics, the sensor revisiting time (the time elapsed between two consecutive interferometry observations of the same area by a sensor) plays a key role in the satellite capability to detect deformation phenomena over time. The revising time, together with the synthetic aperture radar (SAR) wavelength, influences the detectable velocity of the deformation phenomena, which is limited by the ambiguous nature of the interferometric products. In this sense, the ESA Sentinel mission represents a step forward in the field of satellite SAR sensors; the mission is made by a constellation of two satellites, Sentinel-1A and Sentinel-1B, launched in April 2014 and April 2016, respectively. They are able to provide large-scale mapping (250 km swath and 165 km azimuth width) with short revisiting times (down to six days) and are equipped with a C-band sensor.

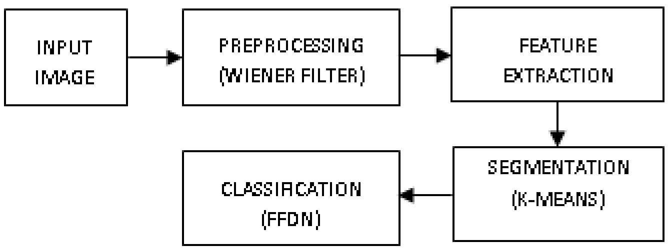

Fig.3.1 Proposed Block Diagram

The input image has been sent for preprocessing. The Wiener filter was employed for preprocessing. It is used to remove noise from the distorted signal and estimate the underlying signal of interest. The preprocessed image is then moved to the feature extraction stage. Feature extraction assists in reducing the amount of redundant data in a data source. K-means is used to segment data. The segmented data is transferred for classification. In classification, a feed forward neural network (FNN) is used.

PREPROCESSING

Image pre-processing is the term for operations on images at the lowest level of abstraction. These operations do not increase image information content but they decrease it if entropy is an information measure. The aim of pre-processing is an improvement of the image data that suppresses undesired distortions or enhances some image features relevant for further processing and analysis task.

Pixel brightness transformations (PBT)

Brightness transformations modify pixel brightness and the transformation depends on the properties of a pixel itself. In PBT, output pixel's value depends only on the corresponding input pixel value. Examples of such operators include brightness and contrast adjustments as well as colour correction and transformations. Contrast enhancement is an important area in image processing for both human and computer vision. It is widely used for medical image processing and as a pre-processing step in speech recognition, texture synthesis, and many other image/video processing applications.

Gamma Correction

Gamma correction is a non-linear adjustment to individual pixel values. While in image normalization we carried out linear operations on individual pixels, such as scalar multiplication and addition/subtraction, gamma correction carries out a non-linear operation on the source image pixels, and can cause saturation of the image being altered.

Histogram equalization

Histogram equalization is a well-known contrast enhancement technique due to its performance on almost all types of image. Histogram equalization provides a sophisticated method for modifying the dynamic range and contrast of an image by altering that image such that its intensity histogram has the desired shape. Unlike contrast stretching, histogram modelling operators may employ non-linear and non-monotonic transfer functions to map between pixel intensity values in the input and output images.

WIENER FILTER

The Wiener filter can be used to filter out the noise from the corrupted signal to provide an estimate of the underlying signal of interest. The Wiener filter is based on a statistical approach, and a more statistical account of the theory is given in the minimum mean square error (MMSE) estimator article. The goal of the Wiener filter is to compute a statistical estimate of an unknown signal using a related signal as an input and filtering that known signal to produce the estimate as an output. For example, the known signal might consist of an unknown signal of interest that has been corrupted by additive noise. The Wiener filter can be used to filter out the noise from the corrupted signal to provide an estimate of the underlying signal of interest. Typical deterministic filters are designed for a desired frequency response. However, the design of the Wiener filter takes a different approach. One is assumed to have knowledge of the spectral properties of the original signal and the noise, and one seeks the linear time-invariant filter whose output would come as close to the original signal as possible. Wiener filters are characterized by the following,

1. Assumption: signal and (additive) noise are stationary linear stochastic processes with known spectral characteristics or known autocorrelation and cross-correlation
2. Requirement: the filter must be physically realizable/causal (this requirement can be dropped, resulting in a non-causal solution)
3. Performance criterion: minimum mean-square error (MMSE)

FEATURE EXTRACTION

Feature extraction is a part of the dimensionality reduction process, in which, an initial set of the raw data is divided and reduced to more manageable groups. So when you want to process it will be easier. The most important characteristic of these large data sets is that they have a large number of variables. These variables require a lot of computing resources to process. So Feature extraction helps to get the best feature from those big data sets by selecting and combining variables into features, thus, effectively reducing the amount of data. These features are easy to process, but still able to describe the actual data set with accuracy and originality. The technique of extracting the features is useful when you have a large data set and need to reduce the number of resources without losing any important or relevant information. Feature extraction helps to reduce the amount of redundant data from the data set. In the end, the reduction of the data helps to build the model with less machine effort and also increases the speed of learning and generalization steps in the machine learning process.

APPLICATIONS OF FEATURE EXTRACTION

- **Bag of Words:** Bag-of-Words is the most used technique for natural language processing. In this process they extract the words or the features from a sentence, document, website, etc. and then they classify them into the frequency of use. So in this whole process feature extraction is one of the most important parts.
- **Image Processing:** Image processing is one of the best and most interesting domain. In this domain basically you will start playing with your images in order to understand them. So here we use many techniques which includes feature extraction as well and algorithms to detect features such as shaped, edges, or motion in a digital image or video to process them.
- Auto-encoders: The main purpose of the auto-encoders is efficient data coding which is unsupervised in nature. This process comes under unsupervised learning. So Feature extraction procedure is applicable here to identify the key features from the data to code by learning from the coding of the original data set to derive new ones.

SEGMENTATION

Image segmentation is a branch of digital image processing which focuses on partitioning an image into different parts according to their features and properties. The primary goal of image segmentation is to simplify the image for easier analysis. In image segmentation, you divide an image into various parts that have similar attributes. The parts in which you divide the image are called Image Objects. It is the first step for image analysis. Without performing image segmentation, performing computer vision implementations would be nearly impossible for you. By using image segmentation techniques, you can divide and group-specific pixels from an image, assign them labels and classify further pixels according to these labels. You can draw lines, specify borders, and separate particular objects (important components) in an image from the rest of the objects (unimportant components). In machine learning, you can use the labels you generated from image segmentation for supervised and unsupervised training. This would allow you to solve many business problems.

K-MEANS SEGMENTATION

K Means is a clustering algorithm. Clustering algorithms are an unsupervised algorithm which means that there is no labeled data available. It is used to identify different classes or clusters in the given data based on how similar the data is. Data points in the same group are more similar to other data points in that same group than those in other groups. K-means clustering is one of the most commonly used clustering algorithms. Here, k represents the number of clusters.

The K-means clustering algorithm attempts to partition a dataset into k clusters, with the i^{th} cluster defined by its centroid μ_i. Each cluster's centroid μ_i is essentially the average value of all n_i points in that cluster.

- The K-means algorithm therefore attempts to find the most appropriate values of the k centroids for the entire dataset using the following steps:
- Randomly choose k data points from the dataset to be the initial k centroid values.
- For each data point in the dataset assign it to the nearest centroid. Distance is measured using the Euclidean distance.
- Recalculate the value of the k centroids as the mean of all n_i data points assigned to it.
- Iterate steps 2–3 until the maximum number of iterations or some tolerance value is reached, or the cluster assignments converge.

DIFFERENT KINDS OF IMAGE SEGMENTATIONS

Image segmentation is a very broad topic and has different ways to go about the process. We can classify image segmentation according to the following parameters:
Approach-Based Classification

In its most basic sense, image segmentation is object identification. An algorithm cannot classify the different components without identifying an object first. From simple to complicated implementations, all image segmentation work based on object identification. So, we can classify image segmentation methods based on the way algorithms identify objects, which means, collecting similar pixels and separating them from dissimilar pixels. There are two approaches to performing this task.

Region-based Approach (Detecting Similarity)

In this method, you detect similar pixels in the image according to a selected threshold, region merging, region spreading, and region growing. Clustering and similar machine learning algorithms use this method to detect unknown features and attributes. Classification algorithms follow this approach for detecting features and separating image segments according to them.

Boundary-based Approach (Detecting Discontinuity)

The boundary-based approach is the opposite of the region-based approach for object identification. Unlike region-based detection, where you find pixels having similar features, you find pixels that are dissimilar to each other in the boundary-based approach. Point Detection, Edge Detection, Line Detection, and similar algorithms follow this method where they detect the edge of dissimilar pixels and separate them from the rest of the image accordingly.

Technique-Based Classification

Both of the approaches have their distinct image segmentation techniques. We use these techniques according to the kind of image we want to process and analyze and the kind of results we want to derive from it. Based on these parameters, we can divide image segmentation algorithms into the following categories:

Structural Techniques

These algorithms require you to have the structural data of the image you are using. This includes the pixels, distributions, histograms, pixel density, colour distribution, and other relevant information.

CLASSIFICATION (FNN)

A Feed Forward Neural Network is an artificial neural network in which the connections between nodes does not form a cycle. The opposite of a feed forward neural network is a recurrent neural network, in which certain pathways are cycled. The feed forward model is the simplest form of neural network as information is only processed in one direction. While the data may pass through multiple hidden nodes, it always moves in one direction and never backwards.

WORKING OF FNN

A Feed Forward Neural Network is commonly seen in its simplest form as a single layer perceptron. In this model, a series of inputs enter the layer and are multiplied by the weights. Each value is then added together to get a sum of the weighted input values. If the sum of the values is above a specific threshold, usually set at zero, the value produced is often 1, whereas if the sum falls below the threshold, the output value is -1. The single layer perceptron is an important model of feed forward neural networks and is often used in classification tasks. Furthermore, single layer perceptrons can incorporate aspects of machine learning. Using a property known as the delta rule, the neural network can compare the outputs of its nodes with the intended values, thus allowing the network to adjust its weights through training in order to produce more accurate output values. This process of training and learning produces a form of a gradient descent. In multi-layered perceptrons, the process of updating weights is nearly analogous, however the process is defined more specifically as back-propagation. In such cases, each hidden layer within the network is adjusted according to the output values produced by the final layer.

APPLICATIONS OF FEED FORWARD NEURAL NETWORKS

While Feed Forward Neural Networks are fairly straightforward, their simplified architecture can be used as an advantage in particular machine learning applications. For example, one may set up a series of feed forward neural networks with the intention of running them independently from each other, but with a mild intermediary for moderation. Like the human brain, this process relies on many individual neurons in order to handle and process larger tasks. As the individual networks perform their tasks independently, the results can be combined at the end to produce a synthesized, and cohesive output.

IV. RESULT AND DISCUSSION

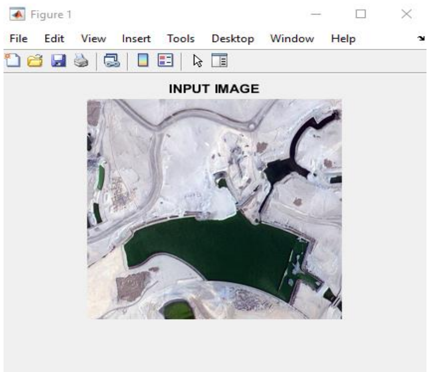

Figure 4.1 Input Image

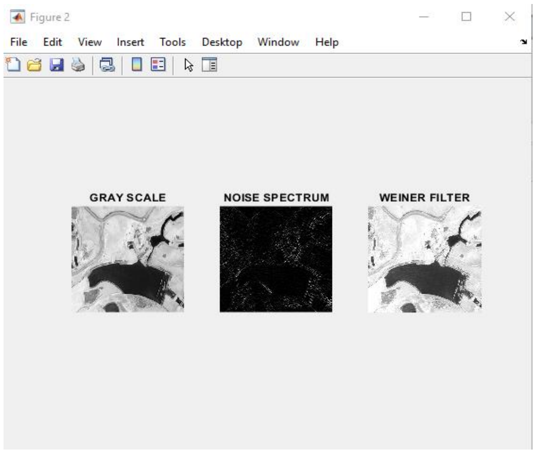

Figure 4.2 Preprocessing

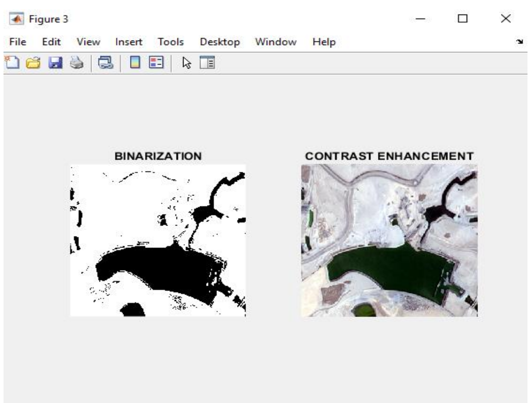

Figure 4.3 Binarization

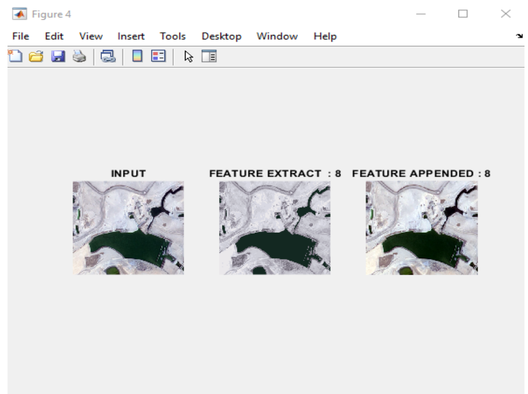

Figure 4.4 Feature Extraction

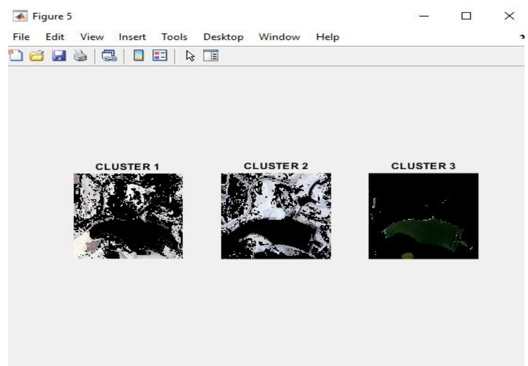

Figure 4.5 Clustering

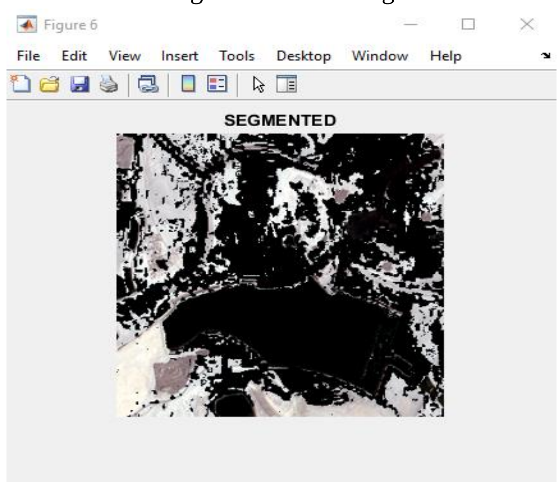

Figure 4.6 Segmentation

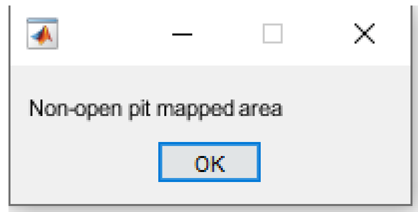

Figure 4.7 Output Image

V. CONCLUSION

Mineral resources are critical to the survival and progress of humanity. The mining and utilization of natural resources has grown increasingly essential in modern times. Mapping the open pit mine areas using feed forward neural network was proposed in this project. The input image has been sent for preprocessing. The Wiener filter was employed for preprocessing. It is used to remove noise from the distorted signal and estimate the underlying signal of interest. The preprocessed image is then moved to the feature extraction stage. Feature extraction assists in reducing the amount of redundant data in a data source. K-means is used to segment data. The segmented data is transferred for classification. In classification, a feed forward neural network (FNN) is used.

REFERENCES

[1] D. Yuan et al., "Assessment of the Ecological Impacts of Coal Mining and Restoration in Alpine Areas: A Case Study of the Muli Coalfield on the Qinghai-Tibet Plateau," in IEEE Access, vol. 9, pp. 162919-162934, 2021.

[2] D. Dong, D. Ming, L. Xu, Q. Qiao and Y. Zhang, "A Stepwise Framework for Fine-Scale Mining Area Types Recognition in Large-Scale Scenes by GF-5 and GF-2 Images," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 16, pp. 5714-5727, 2023.

[3] Zhang, Xiliang, Hoang Nguyen, Xuan-Nam Bui, Quang-Hieu Tran, Dinh-An Nguyen, Dieu Tien Bui and Hossein Moayedi. "Novel soft computing model for predicting blast-induced ground vibration in open-pit mines based on particles warm optimization and XGBoost." Natural Resources Research 29(2020):711-721.

[4] Fan, Xiangsuo, Chuan Yan, Jinlong Fan, and Nayi Wang. "Improved U-Net Remote Sensing Classification Algorithm Fusing Attention and Multi scale Features." Remote Sensing 14, no. 15(2022):3591.

[5] Helleis, Max, Marc Wieland, Christian Krullikowski, Sandro Martinis and Simon Plank. "Sentinel-1-based water and flood mapping: bench marking convolutional neural networks against an operational rule-based processing chain." IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing15(2022):2023-2036.

[6] Deng, Yunjiao, YuleiHou, JiangtaoYan, and Daxing Zeng. "ELU-net: an efficient and lightweight U-net for medical image segmentation." IEEE Access 10(2022):35932-35941.

[7] Chen, Yu, Yongming Wei, Qinjun Wang, Fang Chen, ChunyanLu, and Shaohua Lei. "Mappingpost-earthquake land slide susceptibility: AU-Netlike approach." Remote Sensing 12,no.17(2020): 2767.

[8] Pozaruk, Andrii, Kamlesh Pawar, Shenpeng Li, Alexandra Carey, Jeremy Cheng, Viswanath P. Sudarshan, Marian Cholewa, Jeremy Grummet, Zhaolin Chen, and Gary Egan. "Augmented deeplearning model for improved quantitative accuracy of MR-based PET attenuation correction in PSMAPET-MRI prostate imaging." European Journal of Nuclear Medicine and Molecular Imaging 48(2021):9-20.

[9] Giang, Tuan Linh, KinhBac Dang, QuangToan Le, Vu Giang Nguyen, Si SonTong, and Van-Manh Pham. "U-Net convolutional networks for mining land cover classification based on high- resolution UAV imagery." Ieee Access 8(2020):186257-186273.

[10] Malik, Karim, Colin Robertson, Douglas Braun, and Clara Greig. "U-Net convolutional neural network models for detecting and quantifying placer mining disturb ancesat water shed scales." International Journal of Applied Earth Observation and Geoinformation 104 (2021): 102510.

[11] Liu, Xiaobo, Yuwei Zhang, Hongdi Jing, Liancheng Wang, and Sheng Zhao. "Ore image segmentation method using U-Net and Res_Unet convolutional networks." RSC advances 10, no.16 (2020): 9396-9406.

[12] Gao, Rong, Zhaoyun Sun, Wei Li, Lili Pei, Yuanjiao Hu, and Liyang Xiao. "Automatic coal and gangue segmentation using u-net based fully convolutional networks." Energies13, no.4 (2020):829.

[13] Nava, Lorenzo, Maria Cuevas, Sansar Raj Meena, Filippo Catani, and OriolMonserrat. "Artisanal and small-scale mine detection in semi-desertic areas by improved U-Net." IEEE Geo science and Remote Sensing Letters 19 (2022): 1-5.

[14] Xiao, Dong, Lingyu Yin, and Yanhua Fu. "Open-pit mine road extraction from high-resolution remote sensing images using RATT-UNet." IEEE Geo science and Remote Sensing Letters 19 (2021):1-5

[15] Maxwell, Aaron E., Michelle S. Bester, Luis A. Guillen, Christopher A. Ramezan, Dennis J. Carpinello, Yiting Fan, Faith M. Hartley, Shannon M. Maynard, and Jaimee L. Pyron. "Semantic segmentation deep learning for extracting surface mine extents from historictopographic maps." Remote Sensing12, no.24 (2020): 4145.