

# Hyperspectral signature analysis using neural network for grade estimation of copper ore

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**Abstract.** The ever-increasing demand for the different metal and mineral resources from the earth's subsurface has brought tremendous pressure on the geochemical laboratory for the growing countries. The success of any mining industry relies on the estimated values of ore grade in the mineral deposit. Hence, rapid assessment of ore grade is critical in daily schedule in mines operations. Commonly the assay value is determined by chemical analysis or X-Ray Fluorescence (XRF), which is one of the constrained by real-time grade estimation, duration of sample preparation and processing. Several researches carried out in exploration and revealed that hyperspectral technique is a promising tool for mineral identification and mapping. The goal of the present study is to determine the effectiveness of narrow band spectroscopy in Cu grade estimation. To achieve this, a multilayer feed-forward neural network model has been developed to establish a functional link between hyperspectral signature derived features with the copper grade. Altogether eight different types of features including absorption depth, band depth center, the area under the absorption curve, full width at half maxima were extracted from continuum removed spectra along with derivative reflectance features, e.g. band depth ratio, 1<sup>st</sup> and 2<sup>nd</sup> slopes from the hyperspectral profile. The dimensionality was reduced by applying Principal Component Analysis onto the extracted features. The first seven PCAs are then used as input vector of the ANN model. A five-fold cross-validation exercise is carried out for model performance. The high degree of correlation reveals that the PCA generated feature from hyperspectral data coupled with ANN model could be an alternative approach to predict the copper grade for the copper mine.

**Keywords:** copper grade, spectral feature, principal component analysis, artificial neural network, ore grade estimation, K-Fold cross validation

## 1. Introduction

Artificial Neural network, a machine learning technique is a well-known tool towards automation of routine work in sophisticated industries. In contrast to traditional methodology, sensor-based machine learning systems are being popular to reduce the risk of manual intervention, improve the speed and reliability of grading, and ultimately, reduction of production costs. This sensor based modern technology is also used for automated quality monitoring in production plants like water treatment plants, tea quality monitoring plant [1], food processing plants, pharmaceuticals, recycling industries, etc. In spite of many advantages, sensor based ore quality estimation and sorting in the mining



industry is still a grey area with a limited number of proven applications [2–5]. The advent of new sensors and increasing throughput of automated grade estimation equipment have created an interest to explore sensor-based grade monitoring in the mining industry. Having several advantages of modern sensor based grade estimation technique still the wet laboratory chemical analysis is in practice. This method is not only time consuming but also labor intensive. Sensor based grade estimation of the copper ore from porphyry copper mines could be an easy real time grade estimation technique in the modern days. For quality monitoring purposes, samples might be taken from different stages of the mining operation, which includes blasting face, concentrator plants, or randomly hand pick samples from the entire mine, even from a dumper or from conveyer belt during dispatching the ore material.

Imaging spectroscopy is a proven method to characterize the mineral composition and abundance and forms an active area of research. This technology is currently operationally being used in the quality monitoring of food, water and other industries also. Earlier researchers [6–9] also reported mineral identification can be done by using hyperspectral signature. Present research focuses on whether the ANN model based grade estimation using hyperspectral data could be an alternative approach to determine the copper grade at an Indian mine.

## **2. Study area**

This study area includes Malanjkhand Copper Mine located at Balaghat District, in the state of Madhya Pradesh, Central India. It is one of the largest open-pit copper mine [10], in Asia, under the control of Hindustan Copper Limited (HCL), with an annual copper ore production of approx. 2 Million Tons (MT). The average copper grade of this production is 1.05% (as on 2013) with the total reserves of nearly 321 MT [11].

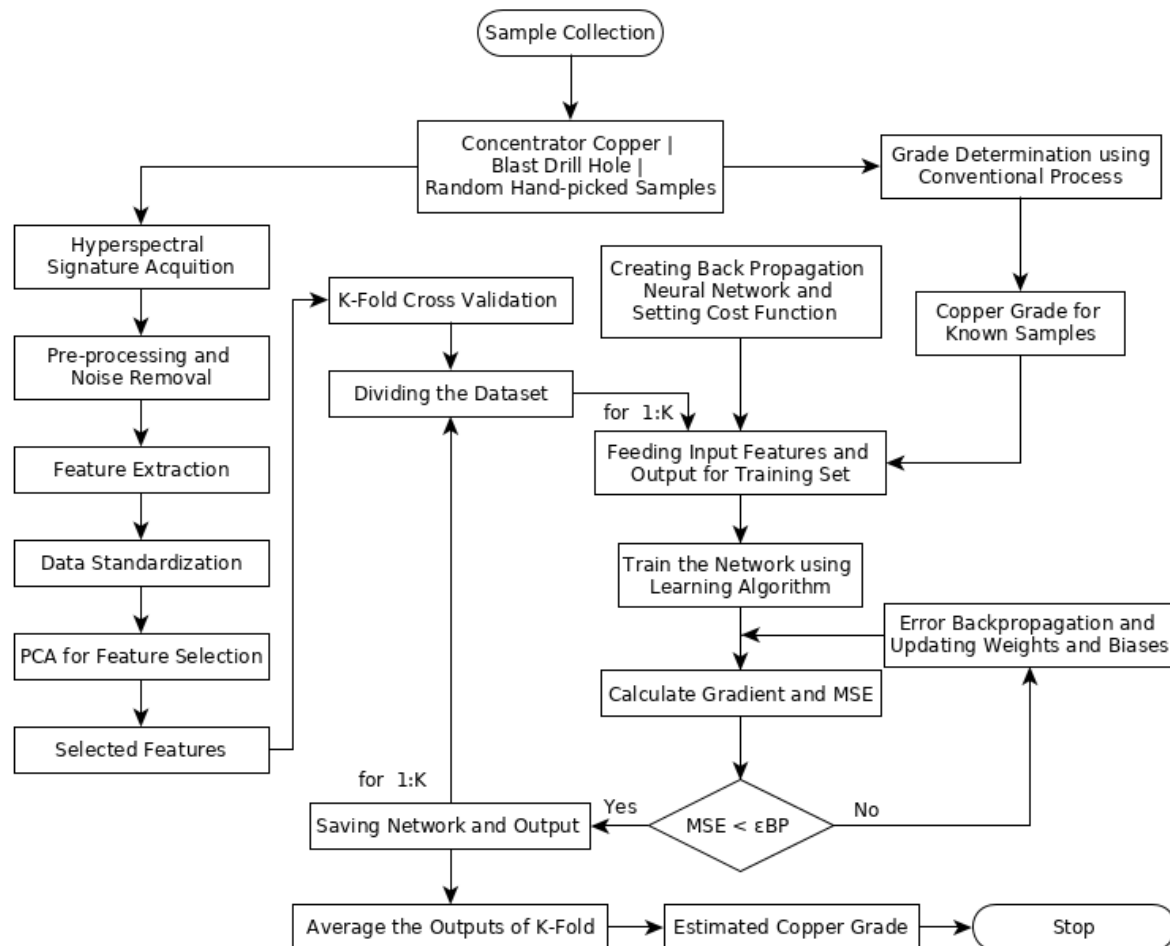
Malanjkhand Copper mine is a porphyry type deposit, with calc-alkaline tonalite-granodiorite plutonic rocks of the early Proterozoic age. The bulk of the mineralization occurs in sheeted quartz-sulfide veins and K-silicate alteration assemblages. The mineralized zone is approximately 2 km in strike length, has a maximum thickness of 200 m and dips 65° along which low-grade mineralization has been traced up to a depth of about 1 km. Primary ores consist essentially of chalcopyrite and pyrite with minor magnetite and Molybdenite [12]. Chalcopyrite, Pyrite and Molybdenite are the primary minerals and the secondary minerals are Chalcocite, Bornite, and Covellite. However, the predominant ore mineral is Chalcopyrite [13]. The ore of Malanjkhand open pit mines have 90% Chalcopyrite ( $\text{CuFeS}_2$ ) and 10% other oxide and sulfate ores.

## **3. Methodology**

The methodology involves sample collection & preparation, hyperspectral signature acquisition, pre-processing of laboratory spectra for detector overlap correction, noise removal, feature identification and attribution, data standardization, data dimensionality reduction using PCA, creation of ANN model and setting its validation algorithm and side by side grade determination in conventional method for training the neural network. The flowchart as shown in Figure 1 is describing the methodology followed in the research study.

### *3.1. Sample collection and preparation*

One hundred fourteen samples collected from three different locations of Malanjkhand Copper Mine viz. Copper concentrator plant, blast drill hole of the mine face and random handpicked samples. The samples are collected in such a way that the grade variation can be obtained in this study. About 500 g each of the samples send to the laboratory and moisture is removed by keeping the samples at open hot air furnace at 105°C temperature for two hrs. Out of 500 g, 50g of the sample is separated using cone and quarter sub-sampling technique and submitted for geochemical analysis to determine the percentage copper content. The rest of the samples are taken for hyperspectral signature acquisition.



**Figure 1.** Flow chart for the methodology of this study

### 3.2. Hyperspectral signature acquisition

SVC HR-1024 spectro-radiometer is used for spectroscopic signature collection from 114 copper samples. The nominal bandwidth is 1.5 nm from 350 to 1000 nm region, 3.8 nm from 1000 to 1890 nm and 2.5 nm from 1890 to 2500 nm. The optics were set at 14° FOV and the distance between the sensor and the object was kept at 20 cm, which covers an area of 20.06 sq. cm at the object plane. It was ensured that the field of view is confined to the spread of the sample which is described in details [14]. Before starting of the spectra acquisition, one reference spectra is taken using spectralon white plate. Each observation was replicated by placing them at 4 different pre-defined angles with an increment of 45° over the horizontal plane to consider BRDF.

### 3.3. Pre-processing and noise removal

Restoring a signal, degraded by additive random noise is a classical problem in signal processing. In the present case also, noise removal, especially from the infrared region, is necessary as many of the mineral spectral absorptions occur in the noisy region. The success of the relating spectral features with mineral abundance depends upon spectral smoothing without compromising the shape of the spectra. Savitzky-Golay (SG) filter was used to suppress the noise, continuum removal and Gaussian fit. To separate out the albedo from the absorption features, continuum removal was carried out which normalizes the spectra. The continuum removal or convex-hull transformation enhances the subtle features and allows comparison of spectra that are acquired by different instruments or under different

light conditions. The continuum is described as a convex hull fitted over the top of a spectrum to connect local spectral maxima. The continuum removed reflectance  $R'_{(\lambda)}$  is obtained by dividing the reflectance value  $R_{\lambda}$  for each waveband in the absorption pit by the reflectance level of the continuum line (convex hull)  $R_{C\lambda}$  [15] at the corresponding wavelength as shown in equation (1).

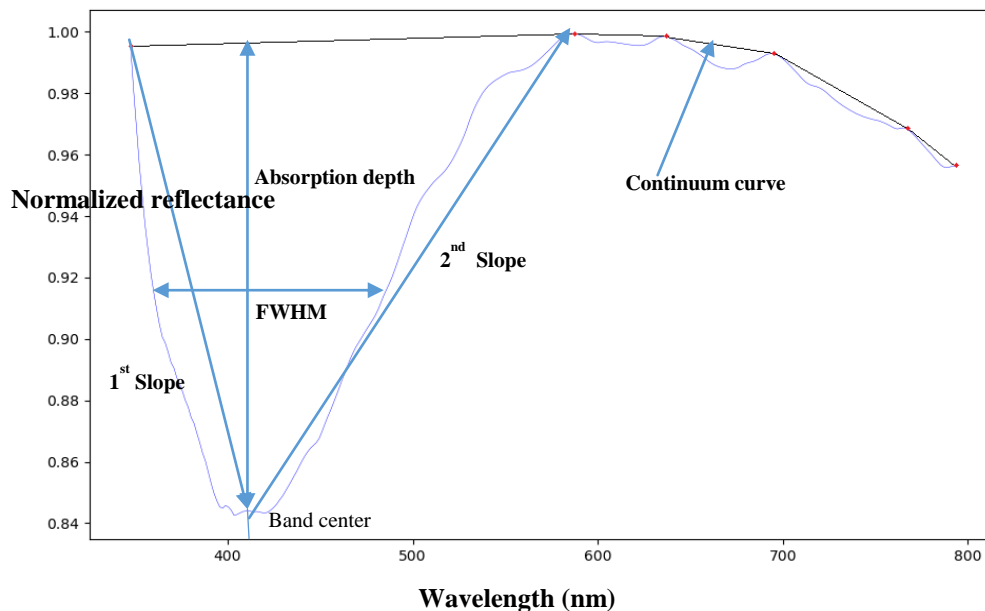
$$R'_{(\lambda)} = \frac{R_{\lambda}}{R_{C\lambda}} \quad (1)$$

After continuum removal, the range of reflectance value becomes 0 to 1 by which the absorption area become enhanced.

### 3.4. Feature extraction

Hyperspectral signatures of copper samples are processed to generate spectral features, which will be used in neural network for model generation. Since these mines have 90% chalcopyrite ( $\text{CuFeS}_2$ ), this study has been focused on only quantifying the grade of  $\text{CuFeS}_2$  using artificial neural network. In the article [14], the absorption band center of  $\text{CuFeS}_2$  is defined at 400 nm indicating the presence of copper due to chalcopyrite. In this study, a range of absorption band from 375 to 425 nm has been considered centered at band depth center of 400 nm. Twenty-five samples out of 114 copper samples have been discarded, as their absorption band center does not fall in the above range. Out of the 89 samples, 26 samples are concentrated samples, 37 samples are blast hole and the rest are handpicked samples.

Eight hyperspectral features viz. Band center, Absorption band depth, Full width at half maximum, Absorption area, 1<sup>st</sup> slope, 2<sup>nd</sup> slope, Continuum Removed Reflectance Spectrum (CRRS), and Band Depth Ratio (BDR) have been extracted from the reflectance spectra [14, 15]. Figure 2 shows a sliced spectral band and the derived spectral features.



**Figure 2.** Convex hull fitting on a sliced and smoothed spectral signature

After feature extraction, feature standardization has been done to scale all feature values to the same range using mean and standard deviation value which is shown in below equation (2).

$$F = \frac{F - \mu}{\sigma} \quad (2)$$

where,  $\mu$  is the mean,  $\sigma$  is the standard deviation and  $F$  is the feature value. After that PCA is performed over the standardized data and first seven features are selected, which comprises 95.07% variance of the total data, which is shown in Figure 4.

### 3.5. Artificial Neural Network

The neural network comprises three layers, one input layer that comprises seven refined feature sets as input features, one output layer comprising of a single node that produces the estimate of the ore and one hidden layer having fifteen nodes.

The network is a feed-forward network. Each node has a set of weights that reflects the ‘importance’ of input features, and a bias value which acts as an intercept to the input function. The output function of each neuron is  $F = W_0 + W_1f_1 + W_2f_2 + \dots + W_nf_n$ . The refined data matrix is faded into the network, where the feature matrix is multiplied with each of the neurons to produce further intermediate dataset. The ANN modelling follow these steps:

Network Framework definition

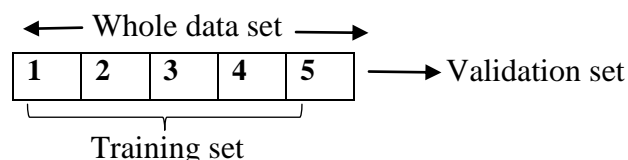
Cost Function for quantifying predictive capability (Mean Square Error)

Training of ANN

Optimization using ADAM Optimizer [16]

Validation using 5-fold cross validation [17]

The parameters are used to make the neural network is shown the below Table 1. The network performance was evaluated by K-Fold cross-validation [18–20] that estimates generalization error based on resampling. Five weight-bias matrices that are generated during 5-fold cross-validation are used to predict five outcomes of the unseen samples. These five outcomes are then averaged to produce the final prediction. Since we are working with such a limited dataset in terms of number of available samples versus available number of workable features (89 samples and 7 principal features), it makes the model prone to over fitting. K-Fold cross-validation will generalized the model to some extent. Here, whole data set is partitioned into five subsets. Of the five subsets, four subsets form the training set while a single subset is used as a validation set as shown in Figure 3.



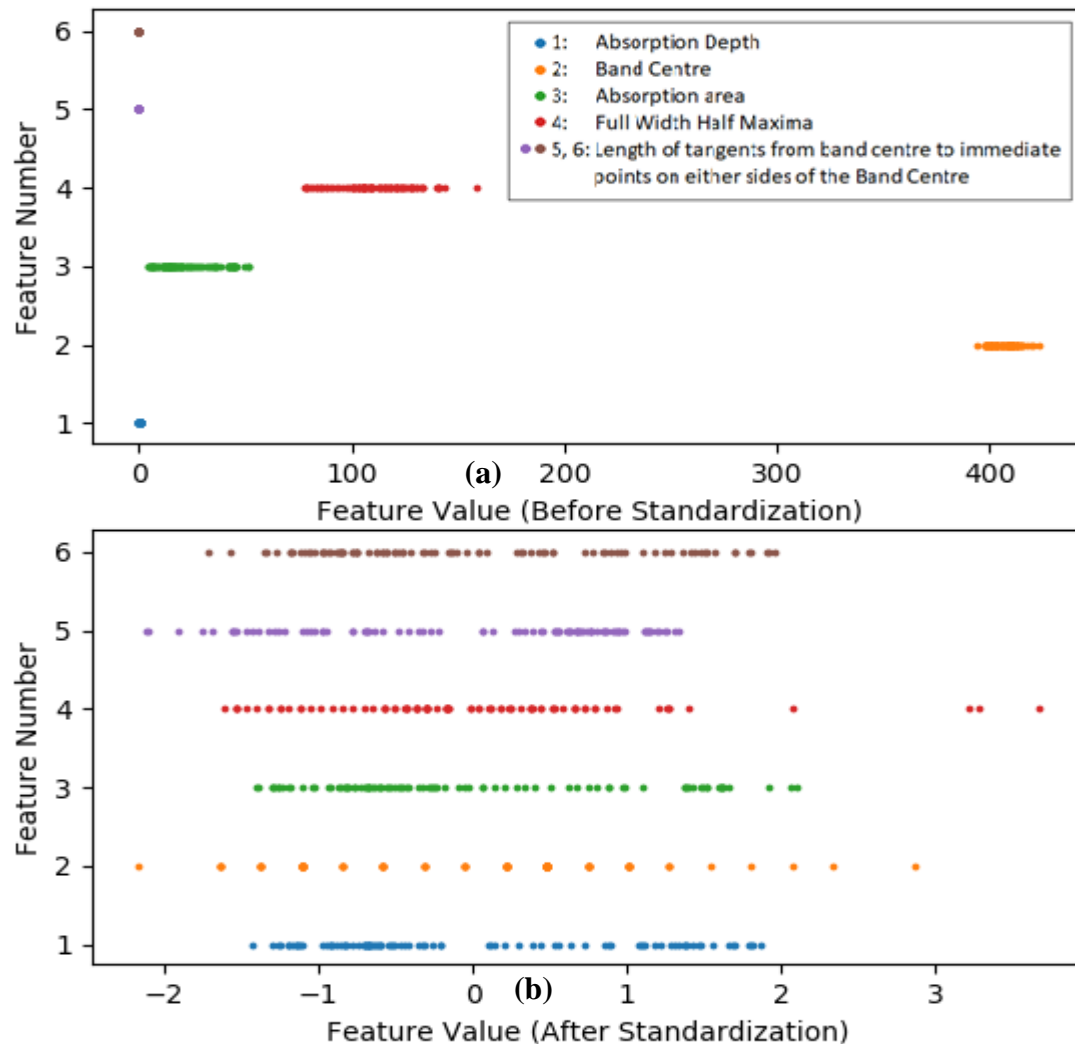
**Figure 3.** Data partitioning in K-Fold for K=5

**Table 1.** ANN parameters for neural network generation

ANN Properties	Properties
Network configuration	[15, 1]
Learning rate	0.001
Training technique	Gradient Descent Backpropagation
Epochs	6000
# Training samples	72 of total number of sample per run
# Validation samples	17 of total number of sample per run
# Input variables	7
Average Validation $R^2$ value	0.89

#### 4. Results and discussion

Finally, eighty-nine samples are analyzed for this study. The range of the derived features are different which is shown in the Figure 4(a) for one sample. Here, it is shown that first six feature values are varying from near 0 to 400. If the untreated data is fed to the neural network, the weights and biases of the network would reflect features with higher weight as features with higher importance, whereas the opposite might be true. That is why standardization has been done which is shown in Figure 4(b).



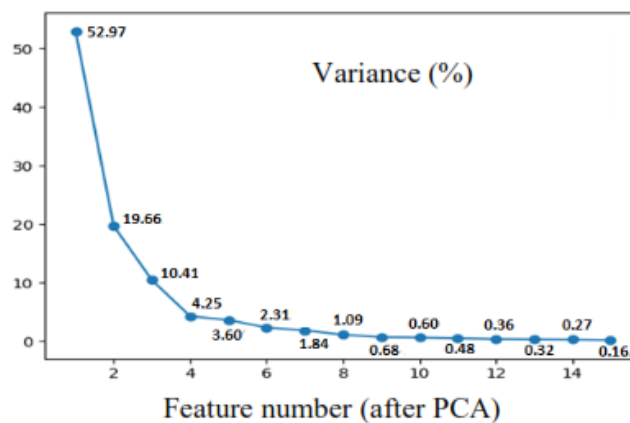
**Figure 4.** (a): Graphical plot of feature values (b): Location of feature values after standardization

Out of eight features that we have considered, first six features are singular and discrete, two are continuous. For the sake of creating a one-dimensional array of features per sample to achieve modest computational complexity, these two types of features are treated as set of multiple features, i.e. treat each data point of the continuous feature as individual feature. By this metric, now the number of elements of the array becomes 314 per sample. This high dimensionality is reduced by PCA. After PCA analysis seven principal features of the feature set have been found to represent 95.07% variance of the total data, which is shown in the below of Figure 5.

Once, the final features are selected for training the ANN module, the three-layer neural network is developed. In this study, ADAM Optimizer based feed-forward back propagation training is used and 5-way (K-Fold) cross validation is used to get final predictive output. At first, randomize the data sets and then partitioned into five parts. In each fold of the cross validation  $k^{\text{th}}$  set used for validation and the rest of all sets are used for training. Each network has been then trained using training set and its performance was evaluated using validation set. The network has been run over 6000 epochs. The best training performance has been taken when the MSE is minimum on the valuation data during training. In Figure 6 shows that the scatter plots for actual vs. estimated values for 5-Fold cross validation using all validation sets. The average  $R^2 = 0.89$  and  $\text{MSE} = 18.12$  which are shown in details in Table 2.

**Table 2.** Performance values of the model

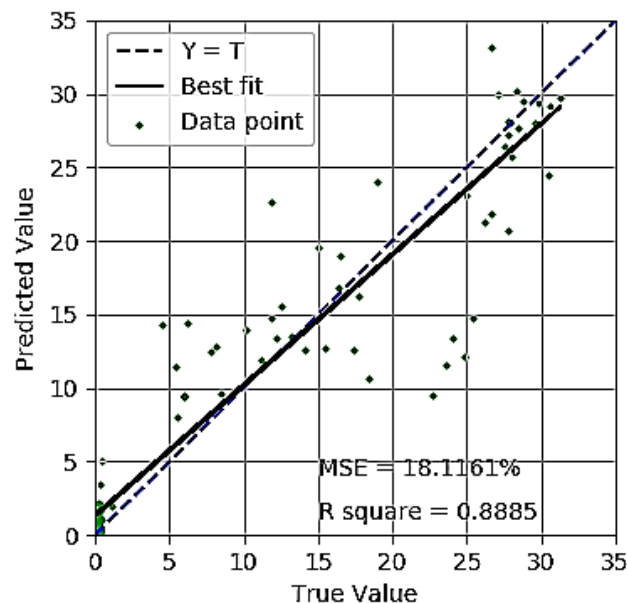
K-Fold cross-validation	Best performance of the Network	
	MSE	$R^2$
K-1	16.37	0.98
K-2	16.57	0.89
K-3	16.42	0.86
K-4	18.92	0.89
K-5	16.36	0.88
Average performance	18.12	0.89



**Figure 5.** Variance percentage of principal features plotted in descending order

At the end of the training, five weight-bias matrix that are generated during 5-way cross validation are used to predict five outcomes of the unseen samples, which are then averaged to produce the final prediction.





**Figure 6.** Scatter plots for actual vs. estimated values for 5-Fold cross validation using all validation sets

## 5. Conclusions

The automatic hyperspectral sensor based grade determination using ANN model of chalcopyrite samples for three different types of copper samples at Malanjkhanda Copper Mine reveals that this method has capability to find out copper grade due to chalcopyrite with  $R^2$  value of 0.89. However, as there is large variation in grade from 0.06 % to 31% and sample size is less, more number of samples are required to implement the technique supplemented by statistical analysis to generalize the model and find out the sensitivity limit of copper grade at which the hyperspectral data performs the best. Sensor calibration is required for real life application also.

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# Corrigendum: Hyperspectral signature analysis using neural network for grade estimation of copper ore

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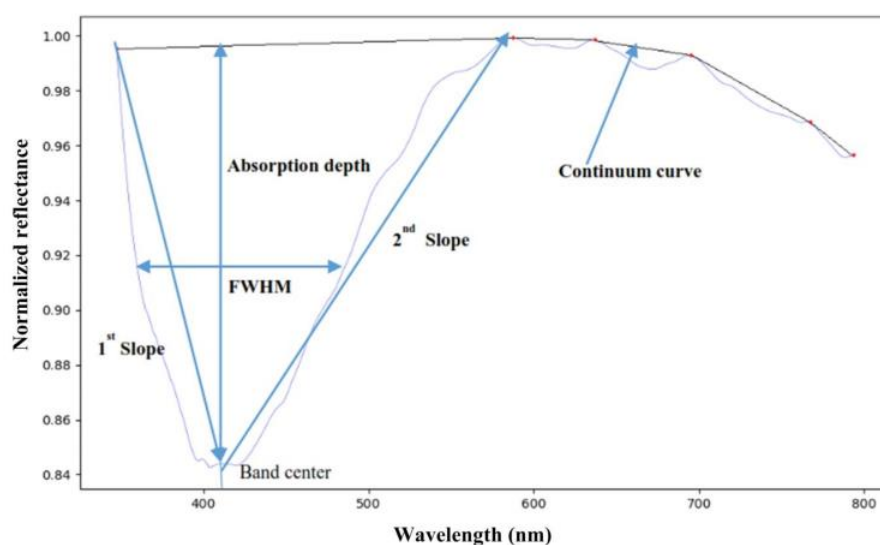
Description of corrigendum is as follows:

## Page 4:

In Figure 2, the y-label “Normalized reflectance” is appears in horizontal orientation.

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“In Figure 2, the y-label “Normalized reflectance” should be in vertical orientation and located in the left”.



**Page 7:**

In Figure 5, the y-label "Variance (%)" is appears moved to the right and in horizontal orientation.

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"In Figure 5, the y-label "Variance (%)" should be in vertical orientation and located in the left.

