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Prediction of Coal Quality Parameters using Digital Image Processing

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Abstract: Quality assessment is of prime importance for the acceptance or rejection of coal in coal-fired power plants. Conventional coal quality assessment methods are time consuming due to the coal preparation and analysis which require multiple equipment. Based on color and texture, rapid coal assessment prediction tools have been developed to minimize the time, expenses and effort of coal assessment. In this research, multi-regression models were developed to predict Fixed Carbon (FC), Ash, and Gross Calorific Value (GCV) from a coal image through Digital Image Processing (DIP) and compared with the conventional coal quality assessment results. The simulation of DIP showed R^2 values for ash vs features 72.6%, fixed carbon vs features is 70.5% and GCV vs features 64.5%. From the results, it can be concluded that the relation between FC and ash with coal image features is more justified than GCV. The R^2 values for Ash and FC were found better and could be used to predict coal quality parameters such as FC and Ash content for a particular coal extracted from Lakhra Coal Mines. Meanwhile, the possibility of this multi-regression models would be validated for various coal samples of indigenous deposits.

Keywords: Coal Quality Parameters, Prediction, Multi-regression model, Image Processing

1 Introduction

Coal is being utilized as a predominant fuel to fulfill the energy requirements in many developed and developing countries [1, 2]. As a result of rapid economic development and industrialization, the energy demands are continuously increasing, especially in economic developing countries (i.e., Pakistan). By the end of 2021, Pakistan government is going to establish new coal-fired power plant to generate cumulative potential of 9491 MW energy using local and imported coal [3]. However, coal-fired power plants in Pakistan still rely on the conventional methods of coal quality assessment using sulfur-carbon analyzer [4], calorific value analyzer [5], and Thermogravimetric analyzer [6], thus making the coal quality assessment process very costly and time-consuming. Therefore, rapid assessment tools for coal quality parameters should be experimented to improve efficacy of coal-fired power plants [7].

The literature reveals that numerous research studies have been conducted to improve the efficiency of coal-fired power plants by achieving rapid assessment of coal quality parameters in order to ensure continuous supply of fuel/coal to power plants [8, 9] because the efficiency of coal power plants significantly affected by coal quality parameters [10]. It is important to note that the prediction of coal quality via digital tools is also considered to be an alternate method of coal assessment in the coal-fired power plants. Therefore, the prediction of coal quality parameters using Digital Image Processing (DIP) can provide an insight for the policy makers to switch from conventional methods of coal assessment to the novel/digital prediction models [11]. For example, Zhang et al. (2014) conducted an important study to predict ash content of coal by image analysis and GA-SVM (Genetic Algorithm-Support Vector Machine) [8]. Qi et al. (2019) used SVR (Support Vector Regression) and sensitivity analysis to predict heating value of blended coal samples [12]. Yerel and Ersen (2013) revealed the effectiveness of a multiple linear regression model by achieving R^2 of about 89.2% for dependent variable (calorific value) using two independent variables (moisture and ash content) [13]. Hadavandi et al. (2017) concluded that carbon, ash, hydrogen, and moisture contents were found to be the most effective variables for the Gross Calorific Value (GCV) prediction [14]. Majumder et al. (2008) developed Higher Heating Value (HHV) prediction models based on proximate analysis, the correlation (R^2) between measured and predicted values was found about 97. 8% [15]. Thereafter, Krishnaiah et al. (2012) developed an elemental analysis prediction model based on the proximate analysis [16]. In this research study, multi-regression model was developed to predict the coal quality parameters such as fixed carbon, ash, and GCV based on the color and texture features for each parameter. Total 35 coal samples were used to acquire the coal images; whereas total 14 colors and 21 texture features were extracted from each acquired coal image. The schematic process of prediction model is illustrated in Figure 1.

2 Materials and Methods

2.1 Site selection and sample collection

For this project, the coal samples were taken from the Indus coal mines located in Lakhra. Lakhra coal is considered as one of the active coal producing fields with

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an average coal seam of 2.43 meters thick and depth of 125 meters located at the western bank of River Indus in the Dadu district. Approximately, 146 million tons of lignite coal was reported to be mined with a considerable variation of calorific value ranging from 5219 Btu/lb to 13555 Btu/lb [17]. The feasibility study was conducted by John T. Boyd & Co. of USA and declared to be a suitable coal composition for power generation [17].

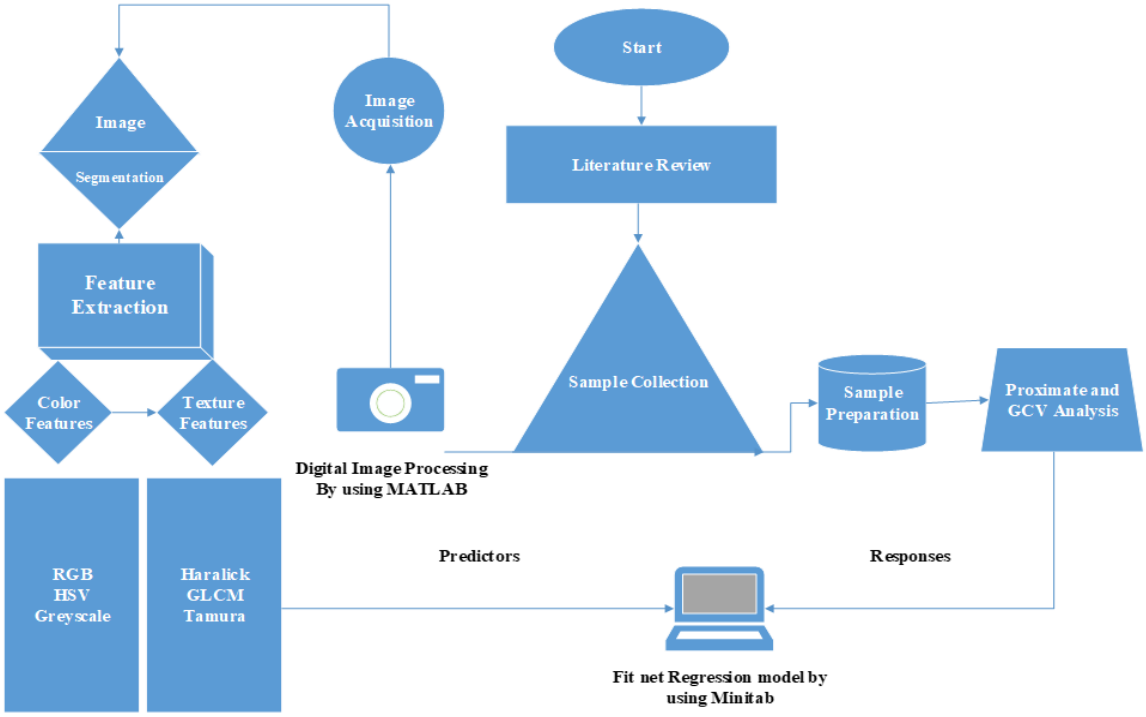

Figure 1. Flow chart of coal quality prediction model

Geological investigation was conducted by many national and international organizations after the first discovery of coal in 1853 but interest was initiated in the early 1960's for the exploration of the large scale coal deposit after the systematic geological investigation performed by GSP and USGS [18].

2.2 System Design and Analysis

For this method first the coal image was acquired to extract the image features and simultaneously some coal particles randomly taken from each sample to analyze by conventional methods. 36 coal samples were taken in which 35 color and texture features were extracted from each coal Image. Fit net Regression model was developed by using Minitab software to developed multi-regression models as shown in **Error! Reference source not found.**.

2.3 Image Acquisition

Image Acquisition is the action of capturing/retrieving an image from some source [19]. Image acquisition can be done by directly connecting your camera to the MATLAB and clicking and inserting image for the processing or by using the workplace of MATLAB and programming one can read and then process it. In this study a box was designed with 2x2x2 ft for image acquisition with two led lights was fixed to make the isolated environment.

2.4 Image Segmentation

Image Segmentation means to divide an image into different sections/regions. In other words, image segmentation deals
with the partitioning of an image in to region of interest as exemplified in the literature [20]. In the literature, following techniques have been applied for Image segmentation in various fields of research [21, 22].

- Thresholding Methods
- Edge based Methods
- Region based Methods
- split and merge Methods
- Clustering methods

In this study, clustering method was used for image segmentation which is considered as one of the most efficient methods in image segmentation, as suggested by various authors [20, 23].

The cluster analysis is to partition an image data set into a number of disjoint groups or clusters Figure 2 shows example of clustering based image segmentation. To segment the coal particles from a coal image two clusters were applied to remove the background as shown in Figure 3.

a b

Figure 2. Example of clustering based image segmentation a Original image b Segmented image [20]

Figure 3. Coal Image Segmentation using clustering technique

2.5 Feature Extraction

An image is comprising of pixels and content some informative features like; color, texture, shape etc. of an object [24]. For this research, two types of feature color features and texture features were extracted to develop prediction models. Total 35 color and texture features are extracted from each coal sample as shown in Figure 4.

2.5.1 Color Features

For Image processing and classification, the most important factor is to extract the efficient features. Color features are widely used for image representation/Classification/Regression models [25]. Mostly, RGB (red, green, and blue), HSV (Hue, Saturation and Value) and gray scale color channels are used for image processing [8] . In this study two color moments are used which shows the color distribution (Mean and Variance).

2.5.2 Texture Features

Texture features contains significant information about the arrangement of the surface. It also defines surface with environment relationship. It also tells the physical composition of the surface. There are different methods of texture feature extraction [26].

2.5.2.1 GLCM Features (Gray Level Co-occurrence Matrix):

GLCM is a matrix when number of rows and columns are equal to number of gray levels [27]. GLCM is developed by distinguish the texture of an image by calculating how repeatedly pairs of pixels with particular values and in a quantified spatial relationship occur in an image. At the end statistical measures were extracted from the developed matrix as shown in Figure 5.

2.5.2.2 Haralick Features:

Haralick features were calculated from four GLCM matrices, 13 textural features are computed that are based on some statistical theory. All these 13 statistical features needs a separate blog post [28].

2.5.2.3 Tamura Features:

Tamura features are based on the psychophysical studies of the characterization elements that are perceived in texture by humans [29].

3 Results and Discussion

To save time and cost in mining industry are the main aspects. Digital image processing and multi-regression models could be the main tools to create coal quality prediction models. In this study, digital image processing and multi-regression analysis was applied to develop coal quality prediction models between dependent variables (Fixed Carbon, Ash, and GCV) and independent variables (Color and Texture Features). The multi-regression equations were developed by using Minitab Software which is given by equations (1), (2), and (3). By using these models/Equations Fixed Carbon, Ash, and Calorific value were predicted and the relation between the actual and predicted values is given in Figure 6, Figure 7 and Figure 8 In prediction models, the R^2 values for Ash vs Features are 72.6%, For Fixed Carbon vs Features is 70.5% and for GCV vs Features 64.5%. From the obtained results it is revealed that the relation between Ash vs Image Features and Fixed Carbon vs image features gives a good relationship.

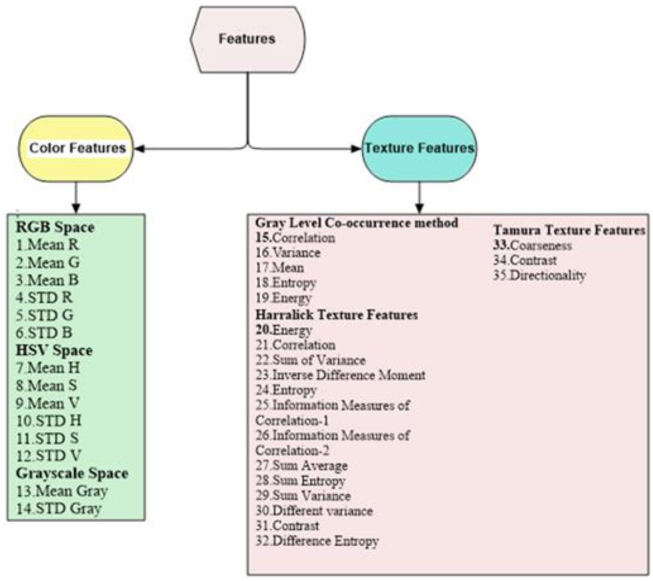

Figure 4 Coal Image Features

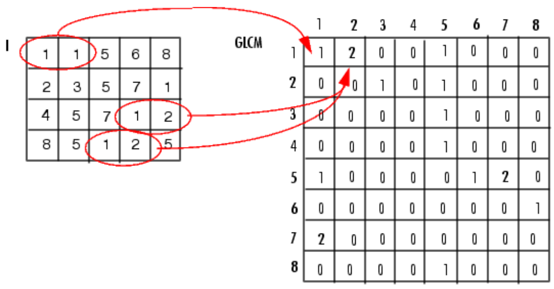

Figure 5 Process used to create GLCM [30]

$$\textbf{Fixed Carbon} = 236772 - 18303\text{Mean H} - 1655\text{ Mean S} - 1273\text{ Mean V} + 3844\text{ Mean Gray} - 719\text{ STD H} - 1077\text{ STD S} - 487\text{ STD V} + 2185\text{ STD Gra} + 5718\text{Correlation} + 0.94\text{ Variance} + 17306\text{ Mean} + 5723\text{ Entropy} + 41513\text{ Energy} - 18467\text{Enrg} - 14707\text{ Corr} - 1162\text{ Sum of Varr} + 33971\text{ Inv Diff MoM} - 261365\text{ Entr} - 2187\text{ Infor Meas of Corr} - 1 - 6023\text{ Infor Meas of Corr} - 2 + 9442\text{ Sum Avg} - 30160\text{ Sum Ent} + 183385\text{ Sum Varr} - 6594\text{ Diff Varr} - 1638\text{ Cont} - 3714\text{ Diff Ent} + 4.8\text{ Coar} - 0.94\text{ Cont}_1 - 0.78\text{ Dire} \quad (2)$$

$$\textbf{Calorific Value} = 10448546 + 230904\text{ Mean H} + 203218\text{ Mean S} - 13953\text{ Mean V} - 289633\text{ Mean Gray} + 16368\text{ STD H} + 41139\text{ STD S} - 8364\text{ STD V} - 49921\text{ STD Gray} + 228589\text{ Correlation} - 104396\text{ Corr} - 1927\text{ Sum of Varr} - 411513\text{ Inv Diff} + 7.4\text{ Variance} - 128986\text{ Mean} + 200753\text{ Entropy} + 614220\text{ Energy} - 885828\text{ Enrg MoM} - 13020594\text{ Entr} + 59170\text{ Infor Meas of Corr} - 1 + 103061\text{ Infor Meas of Corr} - 2 + 1265273\text{ Sum Avg} - 1048555\text{ Sum Ent} + 168380 \quad (1)$$

$$\textbf{\textit{Ash Content}} = 56840 - 12773\text{ MEAN H} - 3107\text{ MEAN S} - 611\text{ MEAN V} + 5309\text{ MEAN GRAY} - 254\text{ STD H} - 456\text{ STD S} - 95\text{ STD V} + 792\text{ STD GRAY} + 493\text{ CORRELATION} + 0.115\text{ VARIANCE} + 11149\text{ MEAN} + 970\text{ ENTROPY} + 15085\text{ ENERGY} - 5674\text{ ENRG} - 6549\text{ CORR} - 443\text{ SUM OF VARR} + 18863\text{ INV DIFF MOM} - 58941\text{ ENTR} - 1726\text{ INFOR MEAS OF CORR} - 1 - 3734\text{ INFOR MEAS OF CORR} - 2 - 9778\text{ SUM AVG} - 3572\text{ SUM ENT} + 36088\text{ SUM VARR} - 3459\text{ DIFF VARR} - 315\text{ CONT} - 813\text{ DIFF ENT} + 1.14\text{ COAR} - 0.36\text{ CONT}_1 - 0.310\text{ DIRE} \quad (1)$$

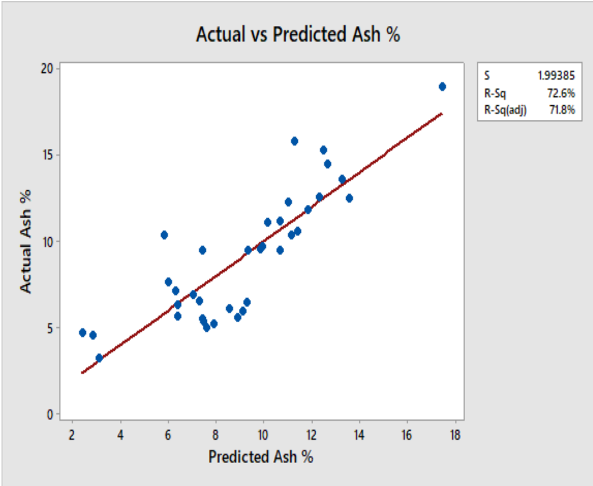

Figure 6 Correlation Between Actual vs Predicted Ash %

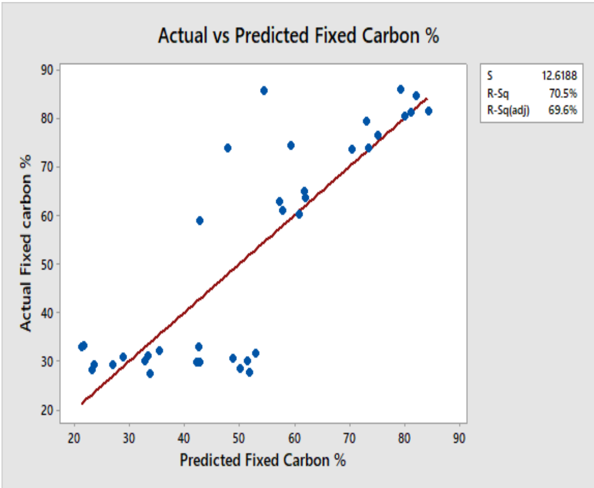

Figure 7 Correlation Between Actual vs Predicted Fixed Carbon %

4 Conclusion

Coal is the most abundant resource for power generation but at the same time it also creates hinders in power plant due to the presence of different constituents. For that coal quality assessment on time is on priority. Traditional methods are time-consuming and are very costly. In this research, multi-regression models were created to predict Fixed Carbon, Ash, and GCV from a coal image. The R^2 values for Ash vs Features are 72.6%, For Fixed Carbon vs Features is 70.5% and for GCV vs Features 64.5%. From the results, it is concluded that the relation between FC and ASH with Coal Image Features is stronger than GCV. The R^2 values for Ash and FC are good and identify the valid models.

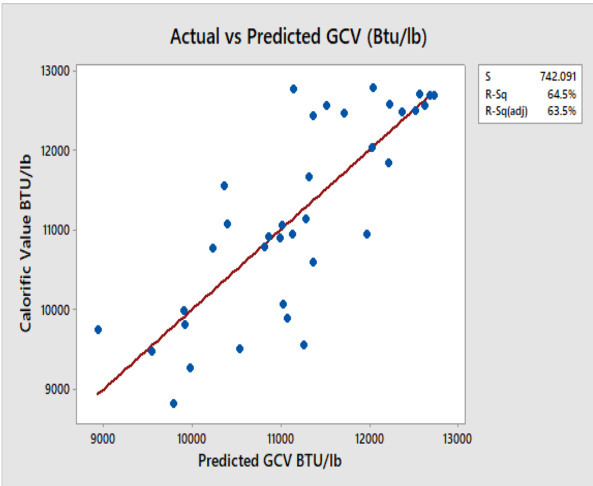

Figure 8 Correlation Between Actual vs Predicted GCV BTu/lb

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