

RAPID PREDICTION OF COAL QUALITY PARAMETERS FROM DIGITAL IMAGES USING MULTIPLE REGRESSION AND ARTIFICIAL NEURAL NETWORKS: A COMPARATIVE STUDY ON LAKHRA LIGNITE

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Abstract

Coal quality assessment governs the acceptance, blending, and combustion control of feedstock in coal-fired power plants, yet the conventional proximate and calorific analyses on which it relies are slow, equipment-intensive, and ill-suited to real-time process control. This study develops and compares two data-driven models that predict the three most decision-relevant coal-quality parameters, namely ash content, fixed carbon (FC), and gross calorific value (GCV), directly from a digital image of the coal, eliminating the day-long laboratory turnaround. Thirty-six lignite samples were collected from the Lakhra coalfield (Sindh, Pakistan); each sample was imaged in a controlled illumination box, segmented by K-means clustering, and characterised by thirty-five colour and texture descriptors drawn from colour moments and the GLCM, Haralick, and Tamura families. The same samples were analysed by a thermogravimetric analyser (TGA-701) and a calorific-value analyser (AC-500) to obtain reference values. A multiple-regression model (MRM) and a two-hidden-layer artificial neural network (ANN) trained with Bayesian regularisation were then fitted to map image features onto coal quality. The ANN clearly outperformed the regression baseline, raising the coefficient of determination from 0.726, 0.705, and 0.645 (MRM) to 0.963, 0.944, and 0.928 (ANN) for ash, FC, and GCV respectively, while reducing mean square error by one to two orders of magnitude. The results confirm that ash and fixed carbon are more tightly coupled to surface colour and texture than GCV, and that a compact neural network can deliver laboratory-comparable estimates within seconds, offering an inexpensive screening tool for indigenous lignite deposits.

1. INTRODUCTION

Coal continues to underpin global electricity generation and heavy industry, and its products play an increasingly significant part in meeting the energy requirements of rapidly industrialising societies. As economic development accelerates, the demand for affordable and dependable energy grows in parallel, placing the efficiency of coal-preparation and coal-fired power plants under

constant scrutiny. Because coal is a heterogeneous material whose composition varies seam-by-seam and even particle-by-particle, power plants must repeatedly characterise their feedstock to manage combustion efficiency, emissions, and boiler health.

The proximate and ultimate analyses of coal are the primary indicators of its quality.

Conventionally these are obtained with dedicated instruments, namely a sulphur-carbon analyser, a calorific-value analyser, and a thermogravimetric analyser, each requiring careful sample preparation and, collectively, up to a full working day per sample. Such latency is incompatible with on-line process control, where blending and feed-rate decisions must be made continuously. In a modern setting where time and cost savings are paramount, digital image processing (DIP) combined with artificial intelligence offers an attractive route to estimate coal-quality parameters within seconds from nothing more than a photograph of the coal.

Pakistan is endowed with very large coal reserves, of the order of 185 billion tonnes, of which roughly 99% lie in the Sindh province, sufficient, in principle, to support tens of thousands of megawatts of generation for centuries. Yet cement plants, steel mills, and especially smaller industries frequently lack in-house proximate and calorific analysers and must outsource testing to external laboratories, incurring both cost and delay. A rapid, low-cost screening method for coal quality would therefore have immediate practical value for indigenous deposits such as the Lakhra lignite.

1.1 Problem statement

The rapid depletion of fossil-fuel assets and the volatility of oil and gas supply have intensified the search for the efficient use of available resources, of which coal remains the most abundant domestic option. However, the heterogeneity of coal and the cost and slowness of conventional quality assessment hinder its efficient utilisation, particularly in resource-constrained operations. There is, therefore, a clear need for an inexpensive and rapid method that can estimate the key coal-quality parameters, namely ash, fixed carbon, and gross calorific value, without the full conventional analytical chain.

1.2 Objectives and contributions

Against this background, the present work pursues three objectives: (i) to develop a coal-quality prediction model based on digital image processing and multiple-regression analysis; (ii) to develop a corresponding model based on digital

image processing and an artificial neural network (ANN); and (iii) to evaluate and compare the performance of the regression and neural-network approaches on the same data. The principal contribution is a side-by-side, like-for-like comparison of a transparent linear model and a compact non-linear network for image-based coal-quality prediction on a genuine indigenous lignite, together with a quantified assessment of which quality parameters are most amenable to image-based inference.

2. Related Work

Coal quality management is a recurring theme in the mineral processing literature, and a wide range of machine learning and machine vision techniques have been proposed to accelerate it. Zhang and Yang analysed ash content on a moving conveyor belt by machine vision, comparing a radial basis function network, a support vector machine (LIB-SVM), and multiple linear regression, and reported that both the support vector and regression models generalised well [2]. Working at the seam scale rather than the particle scale, Youkuo et al. combined least squares support vector machines with the kriging interpolation method to predict coal seam thickness, noting that the accuracy of the prediction was sensitive to the choice of empirical variogram model [3].

Neural networks have featured prominently in the prediction of coal composition. Yao et al. trained a feed-forward back-propagation network on more than nine hundred coal records to predict hydrogen content, and found that compact architectures of the order of four to twelve hidden units already produced accurate predictions, an observation that motivates the small networks used in the present study [4]. Krishnaiah et al. similarly reported that an artificial neural network outperformed conventional approaches when predicting the ultimate analysis of coal from its proximate analysis [11].

Calorific value has attracted particular attention because it governs combustion performance. Sun et al. combined multivariate linear regression with a support vector machine in a hybrid model for gross calorific value and found the hybrid more

accurate than either component alone [6], while Qi et al. showed that sensitivity analysis driven, genetically optimised support vector regression improved the estimation of low calorific value for blended coals [12]. Hadavandi et al. modelled gross calorific value directly from coal properties using support vector regression and identified carbon, ash, hydrogen, and moisture as the most influential variables [13], which helps to explain why image features that correlate with carbon and ash should also carry information about heating value.

Image based ash prediction is especially well represented. Zhang et al. built an ash content model for coarse coal from image analysis and a genetically optimised support vector machine, extracting tens of colour and texture descriptors and reporting that thinner and larger size fractions were predicted more accurately [1]. Ze-lin et al. processed coal particle images in MATLAB and used thirteen image features as the input to a radial basis function network to predict the washability curve [5]. Zhang estimated the density distribution of coal by weight from particle surface colour and texture features selected through mean impact value and support vector machines [8]. In the context of fine coal and combustion residues, Shi et al. predicted the unburned carbon content of fly ash online using clustering least squares support vector machine models with features selected by a minimal redundancy maximal relevance criterion [7], and Dong et al. developed an integrated estimation model of clean coal ash content for froth flotation based on model updating and multiple least squares support vector machines, reporting a correlation coefficient above 0.93 against measured values [10].

Spectroscopic routes have also been explored, as Wang et al. coupled partial least squares regression with a support vector machine classifier for the rapid analysis of coal properties by near infrared reflectance spectroscopy and obtained more accurate predictions when samples were first sorted into classes [9].

A consistent thread across these studies is the choice of descriptors. Colour information is most often summarised by low order colour moments [15] computed in the RGB, HSI, or HSV colour spaces, while texture is captured through statistical methods such as the grey level co-occurrence matrix, histogram, and wavelet features [14], with the co-occurrence descriptors of Haralick et al. remaining a standard reference for texture characterisation [16]. The segmentation step that precedes feature extraction can be approached through thresholding, edge based, region based, or clustering methods, each with characteristic strengths and weaknesses [17]. The motivation for pursuing this line of work in Pakistan is substantial, since the country holds very large indigenous coal reserves, most of which lie in the Sindh province [18]. What remains comparatively under explored is a controlled comparison of regression and neural network models on a single indigenous lignite using an identical feature set, which is the gap that the present study addresses.

3. Materials and Methods

The methodology pairs a conventional analytical chain, which provides the ground-truth coal-quality values, with a digital-image pipeline that supplies the predictive features. The two streams are then fused in two competing models. The overall workflow is summarised in Figure 1.

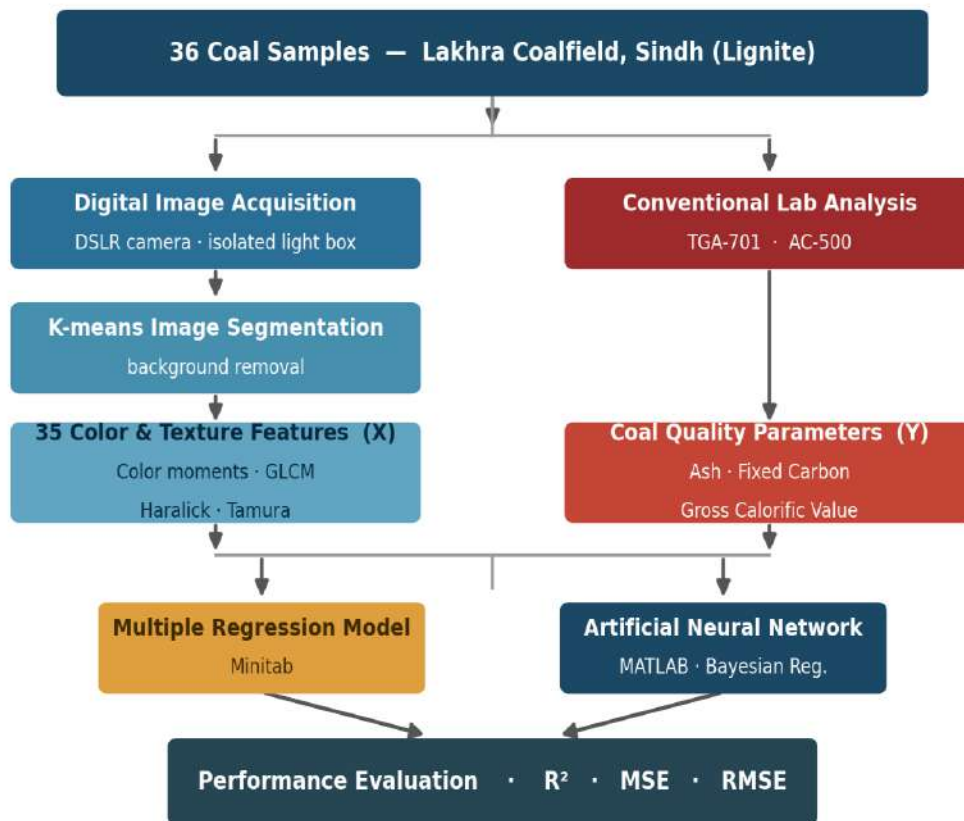


Figure 1. Overall workflow of the image-based coal-quality prediction framework. Each sample is split into an imaging stream (predictors) and a conventional-analysis stream (reference responses) before model fitting and evaluation.

3.1 Study area and sampling

Samples were collected from the Lakhra coalfield, located on the western bank of the River Indus in the Dadu district of Sindh, Pakistan, with material drawn from the Indus Coal Mining Company workings for ease of access. The Lakhra deposit forms a gentle dome-shaped structure, known as the Lakhra Anticline, with strata dipping at about seven degrees; seams are typically around 1.5 m thick beneath 50 to 150 m of overburden. The coal is classified as lignite, with a reported calorific value ranging from roughly 5,200 to 13,600 Btu/lb. Thirty-six representative samples were sealed in air-tight bags and handled carefully to preserve their condition.

3.2 Conventional reference analysis

To establish reference (ground-truth) values, coal particles were randomly drawn from each sample, ground in a mortar and pestle, and sieved to below 250 μm as required by the instruments. Ash and fixed carbon were determined with a LECO thermogravimetric analyser (TGA-701), and gross calorific value was measured with a LECO calorific-value analyser (AC-500), which reports GCV in Btu/lb from a one-gram charge. Both LECO analysers are shown in Figure 2(b) and Figure 2(c). The descriptive statistics of the resulting reference dataset are given in Table 1; the wide spread of ash (3.2 to 18.9%) and fixed carbon (27 to 86%) relative to GCV (coefficient of variation of only 11%) already indicates that GCV is the most narrowly distributed, and therefore the hardest to resolve, of the three targets.

Table 1. Descriptive statistics of the reference coal-quality parameters (N = 32 paired samples).

Parameter	Minimum	Maximum	Mean	Std. dev.
Fixed carbon (%)	27.13	85.80	48.39	22.00
Ash (%)	3.17	18.94	8.45	3.57
Gross calorific value (Btu/lb)	8,803.6	12,768.0	11,147.2	1,225.8

Pairwise correlations among the reference values (FC vs GCV $r = 0.83$, FC vs Ash $r = 0.84$, Ash vs GCV $r = 0.49$) confirm that fixed carbon and ash are strongly interdependent, whereas GCV is only moderately coupled to ash.

3.3 Image acquisition

A purpose-built acquisition box (0.61 m × 0.61 m × 0.46 m) provided a controlled, isolated imaging environment. The interior was lined with non-reflective black cloth, a white sheet was placed at the base, and two 10 W LED lamps supplied diffuse, repeatable illumination. A DSLR camera was suspended at the top of the box and operated

with fixed settings (exposure 0.5, ISO 3200, custom white balance, flash off, single-shot autofocus, 18 MP) so that colour and texture differences between samples reflected the coal itself rather than lighting variation. Coal chunks were crushed and sieved to below 1 mm prior to imaging. The acquisition arrangement is shown in Figure 2(a).

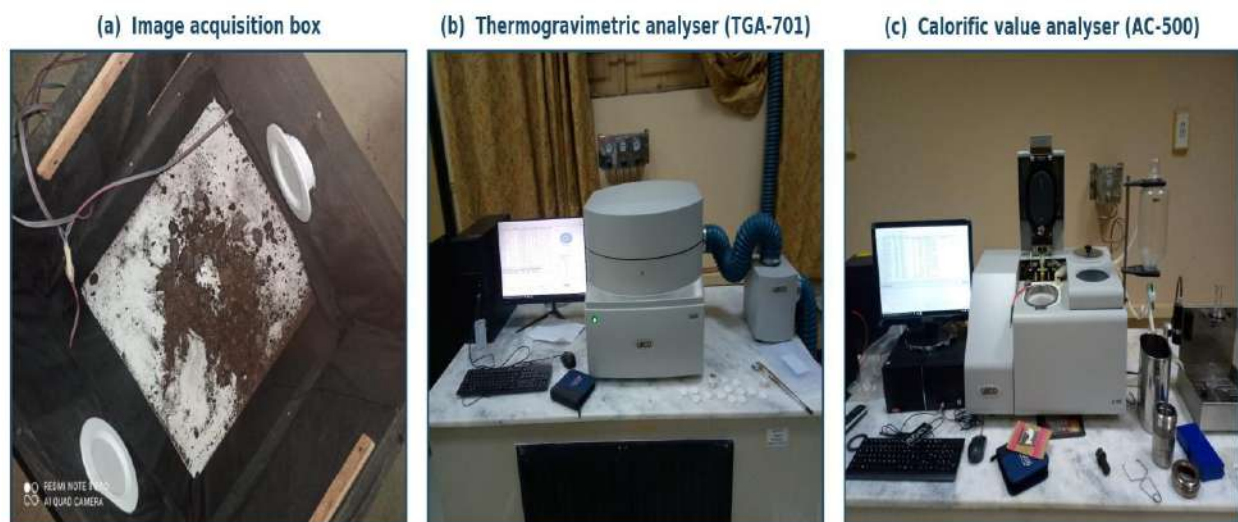


Figure 2. Experimental equipment used in the study: (a) the purpose-built image acquisition box with diffuse LED lighting and a coal sample on the white base sheet; (b) the LECO thermogravimetric analyser (TGA-701) used to obtain ash and fixed carbon; and (c) the LECO calorific value analyser (AC-500) used to obtain gross calorific value.

3.4 Image segmentation

Each acquired image contains both coal particles and background, so segmentation is required before any feature can be meaningfully computed. K-means clustering with two clusters was applied to separate the coal pixels from the background and to suppress the white base sheet, yielding a clean particle mask. Clustering-based segmentation was preferred over thresholding or

edge-based methods because the gradual tonal transitions of fine coal particles are poorly served by hard intensity thresholds or contour detection.

3.5 Feature extraction

Thirty-five colour and texture descriptors were extracted from every segmented image and used as predictors. Colour information was captured through first- and second-order colour moments

(mean and standard deviation) across the HSV, RGB, and grey channels, while texture was characterised through three complementary families: the grey-level co-occurrence matrix (GLCM), Haralick descriptors, and Tamura

descriptors, the last of which are grounded in human texture perception. The full feature set is organised in

Table 2.

Table 2. Composition of the 35-dimensional colour and texture feature vector.

Family	Method	Representative descriptors	Count
Colour	Colour moments	Mean and variance of H, S, V, R, G, B and grey channels	14
Texture	GLCM	Correlation, variance, mean, entropy, energy	5
Texture	Haralick	Energy, correlation, sum/difference variance and entropy, inverse difference moment, information measures of correlation, sum average, contrast	13
Texture	Tamura	Coarseness, contrast, directionality	3
Total	All families	Combined colour + texture predictor vector	35

3.6 Multiple-regression model

The first predictive model is a multiple linear regression (MRM), fitted in Minitab, in which each coal-quality parameter (ash, fixed carbon, GCV) is treated as the response and the thirty-five image descriptors as predictors. Multiple regression is appropriate when a single dependent variable is to be explained by two or more independent variables, and it has the advantage of yielding an explicit, interpretable equation. The three fitted relationships are summarised symbolically in Equations (1) to (3), where each response is a weighted linear combination of the colour and texture features.

$$\text{Ash} = f_{\text{linear}}(\text{colour \& texture features}) \quad (1)$$

$$\text{Fixed Carbon} = f_{\text{linear}}(\text{colour \& texture features}) \quad (2)$$

$$\text{GCV} = f_{\text{linear}}(\text{colour \& texture features}) \quad (3)$$

The complete coefficient sets for the three regression equations were obtained from the fitted models; they are lengthy (thirty-plus terms each) and are retained in the project records for reproducibility.

3.7 Artificial neural network and learning-algorithm selection

The second model is a feed-forward artificial neural network, implemented with the Neural-Network Fitting application in MATLAB. Before fixing the architecture, the choice of training algorithm was examined empirically. Networks were trained for each parameter with two, four, six, eight, and ten hidden neurons under three learning algorithms, namely Levenberg-Marquardt, Bayesian regularisation, and scaled conjugate gradient, and the mean square error (MSE) was recorded. As shown in **Figure 3** and summarised in **Table 3**, Bayesian regularisation produced the lowest and most stable error across all three coal-quality parameters and was therefore selected. Bayesian regularisation minimises a combination of squared errors and weights within a Levenberg-Marquardt framework, which improves generalisation on small datasets such as this one.

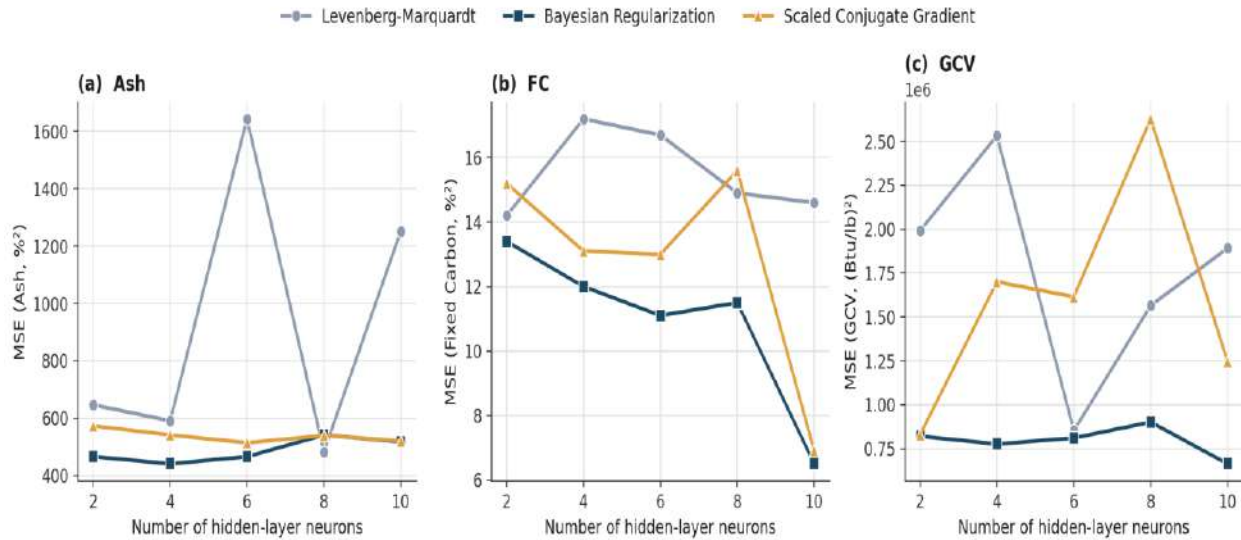


Figure 3. Mean square error of the three candidate learning algorithms as a function of hidden-neuron count for (a) ash, (b) fixed carbon, and (c) GCV. Bayesian regularisation (dark blue) consistently attains the lowest error.

Table 3. Lowest mean square error attained by each learning algorithm (best hidden-neuron count shown in parentheses).

Learning algorithm	Ash	Fixed carbon	GCV
Levenberg-Marquardt	482.4 (8)	14.2 (2)	852,258 (6)
Bayesian regularisation	440.3 (4)	6.5 (10)	663,111 (10)
Scaled conjugate gradient	513.7 (6)	6.9 (10)	828,402 (2)

On the basis of this screening, the final ANN used two hidden layers with sixteen and twenty neurons respectively, trained with Bayesian regularisation, taking the thirty-five image features as inputs and the coal-quality parameter as the single output. All thirty-six samples were used to train, validate, and test the network within the fitting application.

4. Results and Discussion

The thirty-six samples were imaged and analysed as described above, yielding a paired dataset of image features and laboratory coal-quality values. Both the multiple-regression and the neural-network models were then fitted and evaluated against the same reference values. The results are presented model-by-model and then compared directly.

4.1 Multiple-regression model

The regression models reproduce the broad behaviour of all three parameters but leave substantial unexplained variance. The coefficients of determination between measured and predicted values are 0.726 for ash, 0.705 for fixed carbon, and 0.645 for GCV. As **Figure 4** shows, the predicted values track the measured ones but scatter visibly around the 1:1 line, with the spread widening for GCV. The ordering of the three R^2 values already signals that ash and fixed carbon are more strongly governed by surface colour and texture than the calorific value, which depends on chemical composition that is only indirectly expressed in an image.

Measured vs. Predicted – Multiple Regression Model

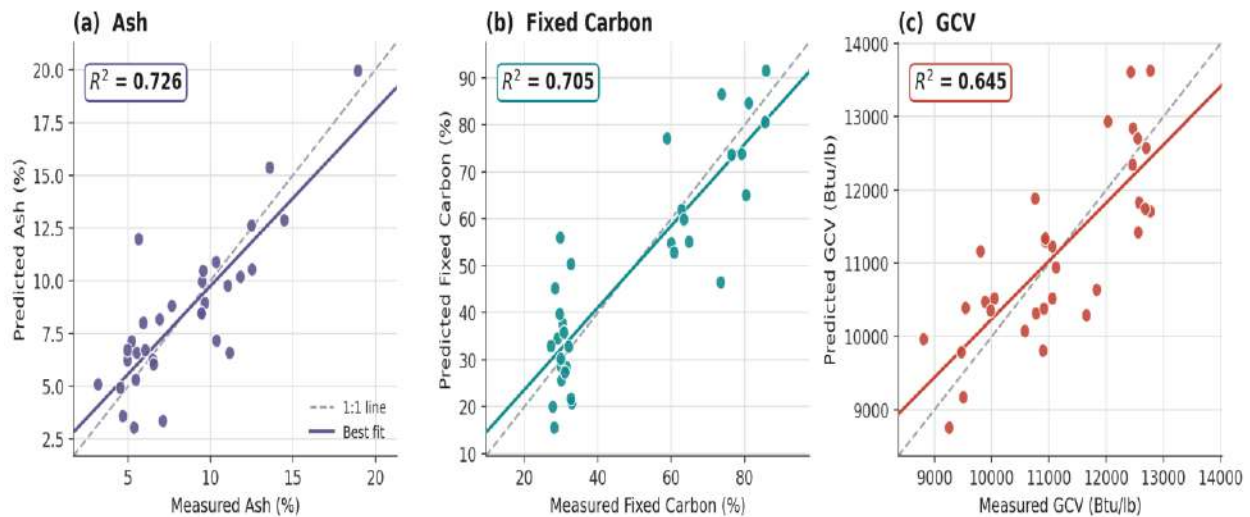


Figure 4. Measured versus predicted values for the multiple-regression model: (a) ash, (b) fixed carbon, (c) GCV. The dashed line is the 1:1 reference; the solid line is the least-squares fit.

4.2 Artificial neural network

The neural network substantially tightens the agreement between measured and predicted values. The coefficients of determination rise to 0.963 for ash, 0.944 for fixed carbon, and 0.928 for GCV. In Figure 5 the points collapse onto the 1:1 line for all three parameters, with only minor

departures for the most extreme samples. The network's capacity to represent non-linear interactions among the colour and texture descriptors is the most plausible explanation for the gain, since the underlying relationship between surface appearance and bulk composition need not be linear.

Measured vs. Predicted – Artificial Neural Network

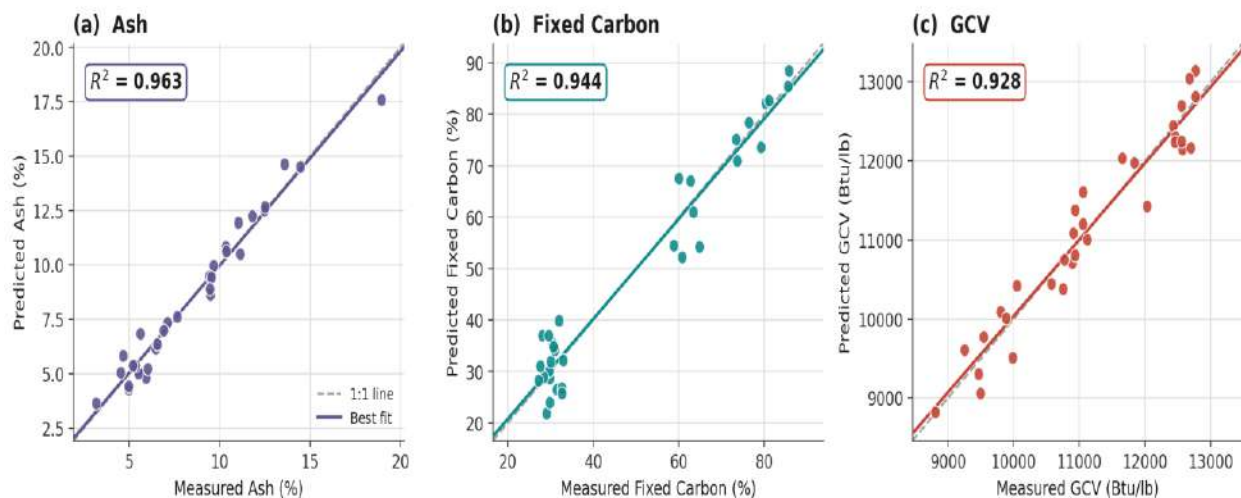


Figure 5. Measured versus predicted values for the Bayesian-regularised ANN: (a) ash, (b) fixed carbon, (c) GCV. Predictions lie close to the 1:1 line for all three parameters.

4.3 Comparative performance

Comparing the two models directly (Figure 6, Figure 7, and Table 4) makes the advantage of the neural network unambiguous. For every parameter the ANN raises R^2 by between 0.24 and 0.28 in absolute terms and reduces the mean square error by one to two orders of magnitude,

falling from 22.7 to 1.7 for ash, from 836 to 77 for fixed carbon, and from 2.92×10^6 to 1.73×10^5 for GCV. Expressed as a root-mean-square error relative to the mean of each parameter, the ANN reduces the relative error from roughly 56% to 15% for ash, from 60% to 18% for fixed carbon, and from 15% to 4% for GCV.

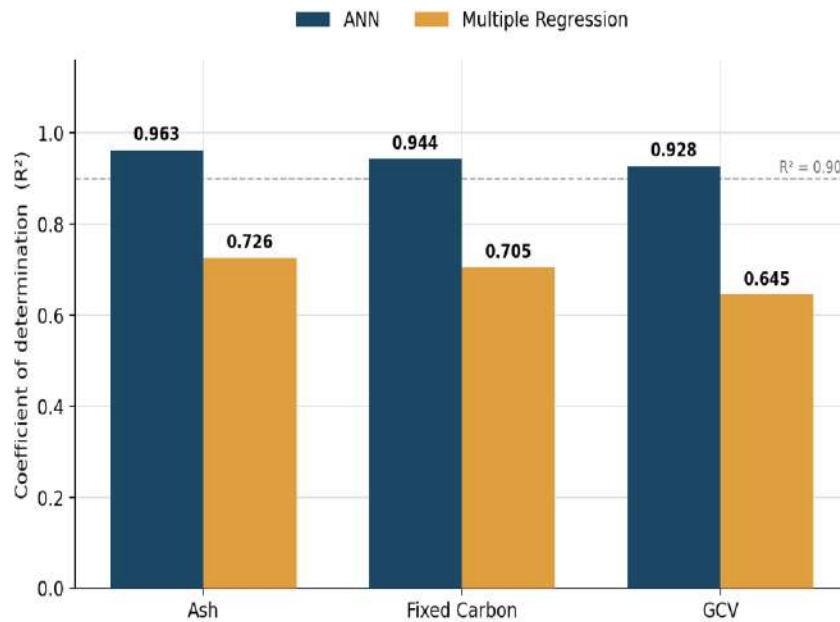


Figure 6. Coefficient of determination (R^2) for the ANN and multiple-regression models across the three coal-quality parameters.

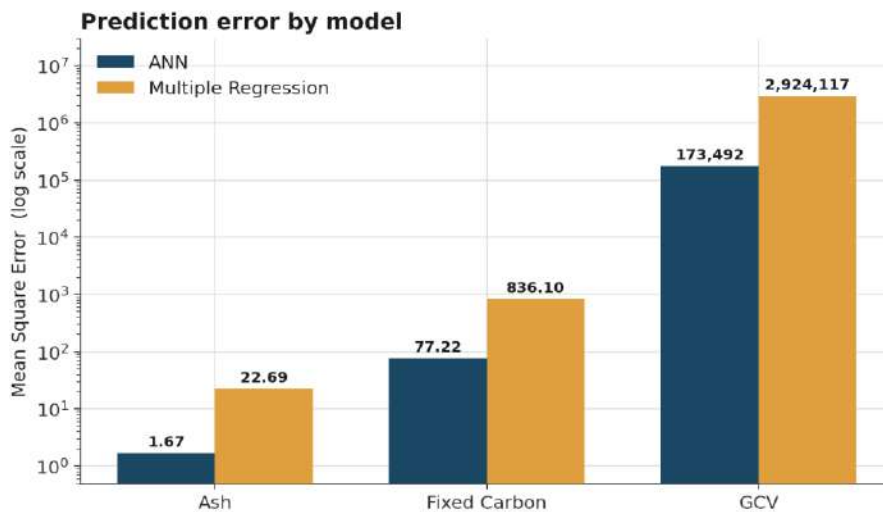


Figure 7. Mean square error (logarithmic scale) for the two models. The ANN reduces error by one to two orders of magnitude for every parameter.

Table 4. Comparative performance of the ANN and multiple-regression models. RMSE is derived as the square root of the reported MSE; relative RMSE is normalised by the parameter mean.

Parameter	Model	R ²	MSE	RMSE	Rel. RMSE
Ash (%)	ANN	0.963	1.67	1.29	15.3%
Ash (%)	MRM	0.726	22.69	4.76	56.4%
Fixed carbon (%)	ANN	0.944	77.22	8.79	18.2%
Fixed carbon (%)	MRM	0.705	836.10	28.92	59.8%
GCV (Btu/lb)	ANN	0.928	173,492	416.5	3.7%
GCV (Btu/lb)	MRM	0.645	2,924,117	1,709.7	15.3%

4.4 Discussion

Three findings stand out. First, across both models the parameters rank consistently in predictability: ash is recovered best, fixed carbon next, and GCV least well. This ordering is physically sensible. Ash and fixed carbon manifest themselves in the visible appearance of coal, since mineral matter brightens and alters the surface texture, while carbon-rich material is darker and more uniform, so that colour and texture descriptors carry direct information about them. Gross calorific value, by contrast, is an integrated chemical property influenced by moisture, hydrogen, and the precise organic composition, only some of which is expressed at the surface; its narrow distribution (coefficient of variation of only 11%) further limits the achievable correlation.

Second, the consistent superiority of the neural network indicates that the mapping from image features to coal quality is genuinely non-linear. The regression model, constrained to additive linear terms, captures the dominant trend but cannot represent interactions between colour and texture; the network, with two modest hidden layers, can. That a network this small generalises well is attributable to the Bayesian-regularisation training, which penalises large weights and thereby resists over-fitting on the limited sample of thirty-six coals.

Third, the practical implication is favourable. With R² above 0.94 for ash and fixed carbon and near 0.93 for GCV, an image-based ANN can serve as a rapid screening tool that returns laboratory-comparable estimates in seconds rather than a day, at negligible marginal cost. This is

particularly relevant for the Lakhra lignite and for smaller operations that cannot justify a full suite of analysers.

Several limitations should temper these conclusions. The models were trained on thirty-six samples from a single coalfield, so the fitted relationships are specific to Lakhra lignite and to the controlled imaging geometry used here; transfer to other ranks, deposits, or field lighting conditions would require re-calibration and a larger, independent test set. The evaluation also relies on within-sample fitting rather than a held-out validation cohort, so the reported accuracies are best read as upper bounds on field performance. These constraints define the agenda for future work rather than diminishing the central result, which is that image-derived colour and texture features carry strong, exploitable signals about ash and fixed carbon and a usable signal about calorific value.

5. Conclusions

This study set out to predict the key coal-quality parameters, namely ash, fixed carbon, and gross calorific value, directly from digital images of coal, and to compare a transparent multiple-regression model with a compact artificial neural network on the same data. Thirty-six lignite samples from the Lakhra coalfield were imaged under controlled illumination, segmented by K-means clustering, and described by thirty-five colour and texture features, with reference values supplied by TGA-701 and AC-500 instruments.

Both models were able to predict the three parameters, but the neural network was decisively

more accurate. The multiple-regression model achieved coefficients of determination of 0.726, 0.705, and 0.645 for ash, fixed carbon, and GCV, whereas the Bayesian-regularised ANN achieved 0.963, 0.944, and 0.928 for the same parameters, while cutting the mean square error by one to two orders of magnitude. Ash and fixed carbon were predicted more reliably than GCV in both models, confirming that these parameters are more directly coupled to the visible colour and texture of coal. Overall, the response of the artificial-intelligence model to image-derived features is clearly superior to that of the regression model, and the approach offers a fast, inexpensive route to coal-quality screening for indigenous deposits.

6. Recommendations and Future Work

The findings of this study suggest several avenues for further investigation. First, the demonstrated accuracy of the image-based neural network invites translation into a deployable instrument: a compact embedded system that integrates a controlled-illumination imaging unit with the trained network could be implemented at coal-fired power plants and preparation facilities to enable continuous, on-line quality screening, thereby reducing reliance on time-intensive laboratory procedures. Second, the generalisability of the approach warrants systematic evaluation. The methodology should be extended to multiple coalfields and coal ranks using a substantially larger and independently partitioned dataset, so that model performance can be assessed on genuinely unseen samples and the transferability of the fitted relationships rigorously quantified. Third, to broaden practical accessibility, the trained model could be deployed within a mobile application, enabling rapid coal-quality estimation by field operators and smaller enterprises that currently depend on outsourced analytical testing.

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