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# Automated Inspection of Char Morphologies in Colombian Coals using Image Analysis

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**ABSTRACT**
Precise automated determination of char morphologies formed by coal during combustion can lead to more efficient industrial control systems for coal combustion. Commonly, char particles are manually classified following the ICCP decision tree which considers four morphological features. One of these features is unfused material, and this class of material not characteristic of Colombian coals. In this paper, we propose new machine learning algorithms to classify the char particles in an image based system. Our hypothesis is that supervised classification methods can outperform the 4 'class' ICCP criteria. In this paper we evaluate several morphological features and specifically assess the contribution of the unfused material feature on the overall classification performance. The results from this work confirm that the proposed method is able to accurately identify and automatically classify chars.

**KEY WORDS**: Char classification, coal combustion, image processing, machine learning, morphological features.

## 1 INTRODUCTION

PULVERISED coal combustion is a two stage process (Cloke & Lester, 1994; Rojas & Barraza, 2007; Stach, 1982; Unsworth, Barratt, & Roberts, 1991). In the first stage, coal particles devolatilise to form char particles. Temperature, residence time, heating rate and the type of coal all influence the char morphologies that are formed. These char morphologies will go on to dictate combustion performance in power plants (Kızgut, Bilen, Toroğlu, & Barış, 2016; Rojas & Barraza, 2008). This is why coal type has a direct impact on combustion performance i.e. poor combustion coals form char particles with morphologies that have poor combustion characteristics.

Commonly, experts classify char samples manually based on the observed morphologies in a char block consisting mainly of resin and char (Bailey, Tate, Diessel, & Wall, 1990). Sectioned char particles are observed through a microscope (with a magnification of 320-500x), counted and classified following the International Committee for Coal and Organic Petrology (ICCP) standard. This standard identifies morphological characteristics, such as unfused material, wall thickness and porosity of particles (Alvarez & Lester, 2001; Lester et al., 2010; Rojas & Barraza, 2008). This process is subjective (because it is done manually) and time-consuming since it is necessary to analyse between 350 and 500 particles per char sample (Rojas & Barraza, 2008; T. Wu, Lester, & Cloke, 2006).

As image analysis tools and microscope hardware have improved over the last 30 years, automation has improved dramatically (Lu & Weng, 2007; Ghiasi-Freez et al., 2014; Caridade et al., 2015; Juang & Wu, 2017; Cervantes et al., 2017; Muhammad Burhan Khan et al., 2018). Systems now exist that can characterise coal automatically based on texture and colour features (Alpana & Mohapatra, 2016), predict coal ash content (Zhang, Yang, Wang, Dou, & Xia, 2014), estimate particle size and particle size

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distribution of fine coal (Igathinathane & Ulusoy, 2016). In a similar way, the analysis of char particles can be automated using image techniques to process (i) high-speed videos of char particles during the coal combustion (Adamczyk et al., 2016; Riaza, Gibbins, & Chalmers, 2017; Schiemann, Vorobiev, & Scherer, 2015) and (ii) char images taken by a digital camera attached to a microscope (Alvarez, Borrego, & Menéndez, 1997; Chaves et al., 2013; T. Wu et al., 2006). In the latter case, the microscopy images are post-processed to automatically identify char particles and quantify morphological characteristics used for assigning a char type using the ICCP decision tree (Lester et al., 2010), such as is shown Figure 1.

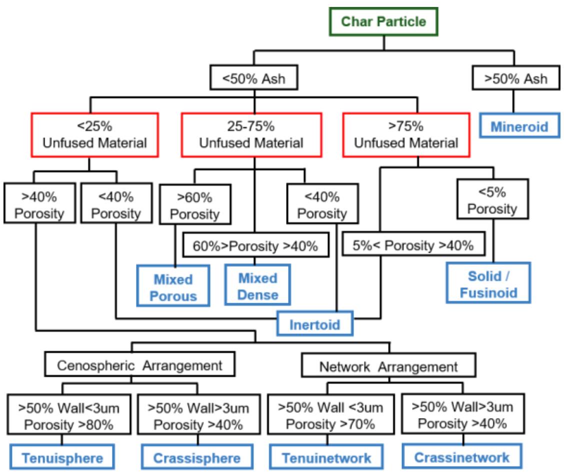


**Figure 1.** ICCP classification of coal chars.

Unfused material is perhaps the most critical feature in the ICCP decision tree. However, char particles from Colombian coals, do not contain high levels of unfused material because the coals themselves tend to only have low levels of the types of inertinite sub-macerals that create unfused structures. e.g. fusinite and macrinite (Sánchez, Rivera, & Velásquez, 2011; Vargas et al., 2013).

We have used a supervised learning approach to automatically learn a new classification criterion for Colombian chars and evaluate the contribution of the unfused material feature in the classification results. Particularly, a general classification model is built using a set of char particles annotated by an expert. First, a feature vector is extracted for each annotated char particle using morphological features. Second, a classifier is trained with the obtained feature vectors. In this work, we build models using three machine learning algorithms. Third, classification of new char particles is performed by using the built classification model.

In this paper, a comparison of the performance of the standard ICCP protocol and automated supervised classification models is conducted using coal samples from Cundinamarca, a region Colombian in the south of Colombia. The hypothesis of this study is focused on addressing the issues of characterising chars from Colombian coals that have low levels of unfused material. A machine learning method may be more accurate in classifying chars than following the decisions as laid out in the traditional ICCP decision tree. Nonetheless, we propose to use more features related to the four standard morphological features for a more reliable description of the images. We also study the contribution of unfused material feature to the supervised classification models.

Section 2 describes the features used to represent the char particle images and the machine learning algorithms used to build the char classification models; Section 3 is focused on experimental evaluation; and Section 4 includes final remarks.

## 2 MATERIAL AND METHODS

THE proposed char classification model is built using image analysis and supervised learning. Given a digital image of chars, a particle segmentation algorithm is used to extract particles present in the image. Initially, each char particle is processed independently by calculating morphological features based on shape descriptors. Later on, a machine learning algorithm is used for building a classifier. The obtained classifier is used to assign a char type/group to a particle under analysis, see Figure 2.

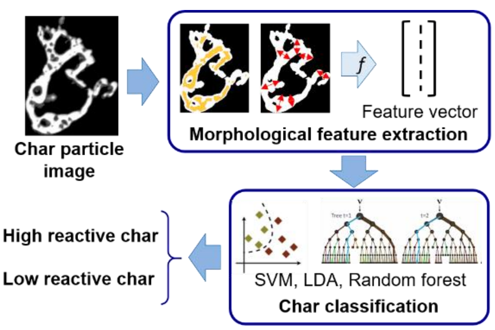


**Figure 2.** Supervised char classification process.

In this paper, two char groups are considered: (i) *high reactive char* have morphologies characterised by high porosity, thin-walls and large superficial area, and (ii) *low reactive char* have morphologies characterised by low porosity, thick-walls and small superficial area. These morphology char groups were defined based on the eight char-types of the ICCP decision tree as illustrated in Figure 3.

### 2.1 Image Acquisition

Coal from Cundinamarca was used to produce char particles. The proximate, ultimate and petrographic analysis of the Cundinamarca coal are presented in Table 1. The proximate analysis determines the thermal energy released when the coal is burnt and predicts how coals will behave when handled and burnt. The ultimate analysis determines the amounts of the principal chemical elements in a coal sample.

The petrographic analysis quantifies the individual organic components of coal (macerals).

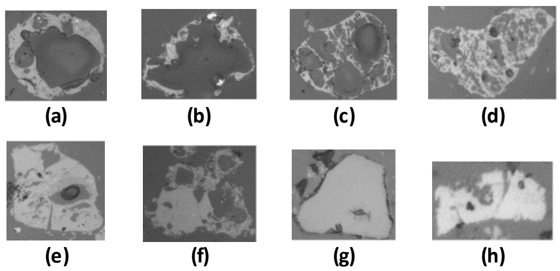


**Figure 3.** **Char morphology groups.** ***High reactive chars:*** **(a) Crassisphere; (b) Teniusphere: (c) Tenuinetwork; (d) Crassisnetwork.** ***Low reactive chars*****: (e) Mixed Porous; (f) Mixed Dense; (g) Solid; (h) Inertoid.**

In particular, Cundinamarca coal is a bituminous coal which is characterised by a high volatile matter and sulphur content with a low amount of liptinite maceral. This kind of coal ignites easily and burns well to generate electricity in coal-fired power plants. However, if burnt improperly it can produce excessive air pollution for unburned carbon when, for instance, the operating conditions are not optimised.

**Table 1.** **Proximate, ultimate and petrographic analysis of the Cundinamarca coal.**

| Proximate Analysis (p/p.%, df.) | |
|---|---|
| Moisture | 2.56 |
| Ash | 12.21 |
| Volatile matter | 35.93 |
| Fixed carbon (calculated by difference) | 49.30 |
| High Heating Value (BTU/lb) | 12670 |
| Ultimate Analysis ( p/p.%, af.) | |
| Carbon | 71.62 |
| Hydrogen | 5.17 |
| Nitrogen | 1.69 |
| Sulphur | 1.45 |
| Oxygen (calculated by difference) | 7.86 |
| Petrographic Analysis (vol.%) | |
| Vitrinite (mmfb) | 65.6 |
| Liptinite (mmfb) | 9.7 |
| Inertinite (mmfb) | 24.8 |

df: dry free; af: ash free; mmfb: mineral matter free basis

We obtained char particles by the devolatilisation process using an entrainment tubular reactor. Coal samples with a particle size of -250µm and a 1% v/v oxygen gas flow used to allow tar oxidation and avoid char particle condensation. Coal particle residence times in the reactor were 100ms, 200ms, 300ms at 800°C, 900°C, 1000°C, respectively with a $10^4$°C/s heating rate. These conditions are similar to the average operating conditions used in industrial pulverised-coal combustion systems (H. Wu et al., 2011).

Char samples from these experiments were mounted in blocks, which are built using char, resin and liquid hardener. The char block surface is polished with fine polishing clothes using suspensions of alumina at 0.5, 0.3 and 0.05 microns. Finally, digital images of 1600x1200 pixels are taken with a camera coupled to a metallographic microscope and 50x magnification lens. The internal 10x objective means that particles are magnified by a total of 500x.

## 2.2 Morphological Feature Extraction

The ICCP decision tree and Colombian coal characteristics are used as a reference for selecting the ten morphological image features listed below (Chaves et al., 2013; Lester et al., 2010; Liu, Cashman, & Rust, 2015):

*Area* is calculated as the number of white colour pixels in a binary char image. The binary image (representing the area char particle) is obtained by the Triangle method (Zack, Rogers, & Latt, 1977), in Figure 4b.

*Unfused material* is measured as the ratio between area unfused material and area char particle. Unfused material corresponds to the brightest grey intensities in char images —in our case intensity values between 250 and 255, in Figure 4c.

*Number of pores* identified in a char particle image, in Figure 4d.

*Porosity* is calculated as the ratio between the area represented by pores and area char particle.

*Sphericity* is the ratio between the minimum and the maximum Feret diameters. The minimum and the maximum Feret diameters correspond respectively to the shortest and the longest distance between any two parallel tangents on a char particle, in Figure 4e. If the two measurements are identical then sphericity is equal to 1.

*Wall thickness* is measured in a binary char image in three steps. First, lines are drawn from the image centre at each direction. For every line, a measure of thickness is calculated as the distance of two intersected points at the particle edges. Second, the histogram of wall thickness is computed (see Figure 4f). Third, the first, second and third quartiles of wall thickness distribution are calculated to represent the particle wall thickness.

*Compactness* is obtained as the ratio between area char particle and bounding rectangle area which surrounds the particle, in Figure 4g.

*Solidity* is calculated as the ratio area char particle and the convex hull area of a particle, in Figure 4h.

*Defect area* is calculated as:

$$\frac{(A_{ch} - Area)}{Area}, \tag{1}$$

where *Area* is the area char particle and $A_{ch}$ is the convex hull area of a particle.

*Roundness* is computed as:

$$\frac{4Area}{\pi DMaxFeret^2}, \tag{2}$$

where *Area* is the area char particle and *DMaxFeret* is the maximum Feret diameter.

Once selected morphological features are computed, a vector is built by concatenating those features. Table 2 presents the six feature vector configurations evaluated in this work. The first feature vector is composed of the features that are used for the ICCP decision tree —the unfused material, the porosity, the sphericity and the second quartile of the wall thickness distribution. In this case, such features are automatically extracted from the grey scale char particle image.

The second feature vector includes, in addition to the previous ones, the area, the number of pores and the first and the third quartiles of the wall thickness distribution of particles.

The third feature vector includes additionally the compactness, the solidity, the defect area and the roundness of char particles.

The fourth, fifth and sixth feature vectors are equivalent to the first, the second and the third configurations respectively, but without considering the unfused material feature.

In this way, we can evaluate two cases: (i) whether, when using an automatic inspection system, by adding more features to the ones proposed by the ICCP results create an improvement; (ii) whether the unfused material feature is a robust feature for Colombian coals as suggested by the ICCP system.

### 2.3 *Char Classification*

Given the set of morphological feature vectors described previously —in Subsection 2.2— and the corresponding label —e.i. *high reactive char* with high porosity, thin-walled and large superficial area and *low reactive char* with low porosity, thick-walled and small superficial area— a machine learning algorithm is used for building a classifier. In this work Support Vector Machine (SVM), Random Forest (RF) and Linear Discriminant Analysis (LDA) algorithms are evaluated.

SVM (Boser, Guyon, & Vapnik, 1992) constructs a hyperplane or set of hyperplanes in a high or infinite dimensional space, which can be used for classification, regression or other tasks. Intuitively, a good separation between classes is achieved by the hyperplane that has the largest distance to the nearest training data points of any class —called functional margin— since, in general, the larger the margin the lower the generalisation error of the classifier. A regularisation parameter *C* controls the tradeoff between maximizing the margin and minimizing the training error.

RF (Criminisi, Shotton, & Konukoglu, 2011) is an ensemble of decision trees. Each decision tree is trained using a subset of the training data. The final classifier corresponds to a combination of individual trees. RF can be summarised in three steps (Criminisi et al., 2011; Tang, Lu, Sun, & Jiang, 2012): (i) choose *T* subsets from training data —*T* is the number of decision trees in the forest; (ii) grow a decision tree, with *D* nodes, for each subset of training data. The best split at each decision tree node is selected using a subset of features; (iii) classify test data by combining the outputs of the *T* trees.

LDA (Fisher, 1936) generates a linear combination of features that best separates two classes by fitting class conditional densities to the dataset and using Bayes' rule. The model fits a Gaussian density to each class, assuming that all classes share the same covariance matrix.

## 3 EXPERIMENTAL SET-UP, RESULTS AND DISCUSSION

EXPERIMENTS were performed on a dataset composed of 1600 char images —800 images correspond to high reactive chars and 800 images correspond to low reactive chars. Morphological features presented in Subsection 2.2 were normalised in order to avoid the effect of different scales. A five-fold cross-validation was employed to make the method able to generalise to independent data sets. The dataset was split into two groups (80% and 20% of the data) which were used as training and testing sets, respectively.

**Table 2. Feature vector configurations used to build the char classification models.**

| Feature Vector # | Features | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Unfused material | Porosity | Sphericity | Wall Thickness | | Area | Num. Pores | Compactness | Solidity | Defect area | Roundness |
| | | | | $Q_2$ | $Q_1,Q_3$ | | | | | | |
| 1 | X | X | X | X | | | | | | | |
| 2 | X | X | X | X | X | X | X | | | | |
| 3 | X | X | X | X | X | X | X | X | X | X | X |
| 4 | | X | X | X | | | | | | | |
| 5 | | X | X | X | X | X | X | | | | |
| 6 | | X | X | X | X | X | X | X | X | X | X |

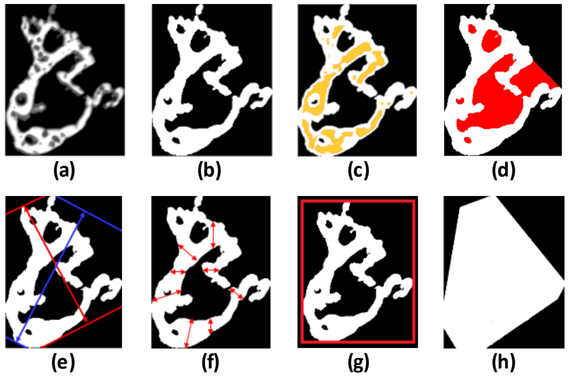


**Figure 4.** **Morphological char features. (a) Char particle image in grey scale; (b) Total area of the particle in white colour; (c) Unfused material in yellow colour; (d) Identified pores in red colour; (e) Illustration of the minimum and maximum Feret diameters in red and blue colours respectively; (f) Line transects used for calculating wall thickness; (g) Bounding rectangle surrounding the particle in red colour; (h) Convex hull area of particle in white colour.**

SVM classification models were trained using a linear kernel with a regularisation parameter $C$=1. RF classifiers were built employing $T$=50 trees. Each tree was grown to a maximum level size $D$=6. The number of features selected to learn the split function is, at each node, equal to $\rho = \sqrt{\tau}$ where the number of features, $\tau$, depends on the feature vector used to train the models.

Table 3 presents the average accuracy (Acc) values and the Area Under the Receiver Operating Characteristic Curve values (AUC) obtained for the SVM, RF and LDA classifiers built using the six vector feature configurations described in Table 2. Acc corresponds to the proportion of char particles correctly classified with respect to the total number of evaluated images (Powers, 2011). AUC corresponds to the probability that a classifier ranked a randomly chosen “high reactive char” example higher than a “low reactive char” one, which indicates how well a feature vector can distinguish among classes (Powers, 2011). Char classifiers with higher Acc and AUC values exhibit better performance.

Figure 5 shows the Receiver Operating Characteristic Curves (ROC) obtained for the SVM, RF and LDA classifiers built using the six vector feature configurations described in Table 2. ROC corresponds to a plot of the true positive rate against the false positive rate when a discrimination threshold is varied. The threshold determines when an example is positive, “high reactive char”, in our case. A classifier is more accurate, the closer the ROC curve follows to the left-hand border and then the top border.

Classification models obtained using the three machine learning algorithms present similar Acc and AUC results (see Table 3 and Figure 5) for each training feature vector suggesting that chosen features allow learning stable classifiers. In particular, char classification models generated by RF show slightly higher accuracy values in comparison to SVM and LDA models.

Experts manually classified the char particle images following the ICCP decision tree. An Acc value of 0.5656 was achieved since chars from Colombian coals are low in unfused material and, as mentioned earlier, fused/unfused is the most important discriminator in the ICCP decision tree. On the other hand, Acc values increased —Acc average between 0.6281±0.0169 and 0.7438±0.0238 and AUC between 0.7266 and 0.8420— when the classification models are built by supervised algorithms employing the first feature vector configuration that is based on the features used by the ICCP decision tree. Machine learning algorithms are able to connect the relationship between particle shape characteristics distinguishing better among the high reactive and low reactive chars. We therefore conclude that computer vision systems can outperform ICCP protocol for chars derived from Colombian coals and, by extension, other coals that produce low levels of unfused material.

A significant increase in Acc performance was observed by taking into account additional shape features to learn the char classification models —the second and the third feature vector configurations with respect to the first one. Models obtained using the second feature vector which included general shape features —the number of pores, the area and the first and the second quartiles of wall thickness particle distribution— improved Acc, obtaining average values between 0.7894±0.0092 and 0.8394±0.0163 with AUC values between 0.8929 and 0.9380. In a similar way, introducing shape features that better describe particle porosity —compactness, solidity and defect area— and particle roundness in the third feature vector allowed more robust models to be built with higher Acc values —Acc average between 0.8506±0.0207 and 0.8730±0.0218 with AUC values between 0.9415 and 0.9627.

Additionally, the effect of unfused material was evaluated on the fourth, fifth and sixth feature vector configurations which do not include this characteristic. The obtained Acc values were similar to the previous three configurations. This suggests that the unfused material does not have a significant effect on the classification of chars from Colombian coals since it does not help to distinguish between high reactive and low reactive chars. Therefore, the unfused material feature can be discarded while evaluating the reactivity of Colombian coals.

## 4 CONCLUSIONS

IN this paper, we present an efficient method for the automated inspection of char morphologies in Colombian coal samples based on computer vision. Char classification models were trained using SVM,

**Table 3.** Acc average and AUC values by classifier: ICCP decision tree, SVM, RF, and LDA. Higher values mean better performance.

| Feature Vector # | Classifier | | | | | | |
|---|---|---|---|---|---|---|---|
| | ICCP tree | SVM | | RF | | LDA | |
| | Acc | Acc ± σ | AUC | Acc. ± σ | AUC | Acc. ± σ | AUC |
| 1 | 0.5656 | 0.6281 ± 0.0169 | 0.7266 | 0.7438 ± 0.0238 | 0.8420 | 0.6331 ± 0.0202 | 0.7300 |
| 2 | | 0.8081 ± 0.0149 | 0.9007 | 0.8394 ± 0.0163 | 0.9380 | 0.7894 ± 0.0092 | 0.8929 |
| 3 | | 0.8694 ± 0.0281 | 0.9526 | 0.8731 ± 0.0218 | 0.9627 | 0.8506 ± 0.0207 | 0.9415 |
| 4 | | 0.6281 ± 0.0169 | 0.7263 | 0.7144 ± 0.0217 | 0.8017 | 0.6313 ± 0.0223 | 0.7304 |
| 5 | | 0.8081 ± 0.0164 | 0.9002 | 0.8500 ± 0.0201 | 0.9467 | 0.7894 ± 0.0092 | 0.8896 |
| 6 | | 0.8688 ± 0.0248 | 0.9520 | 0.8700 ± 0.0213 | 0.9599 | 0.8506 ± 0.0207 | 0.9414 |

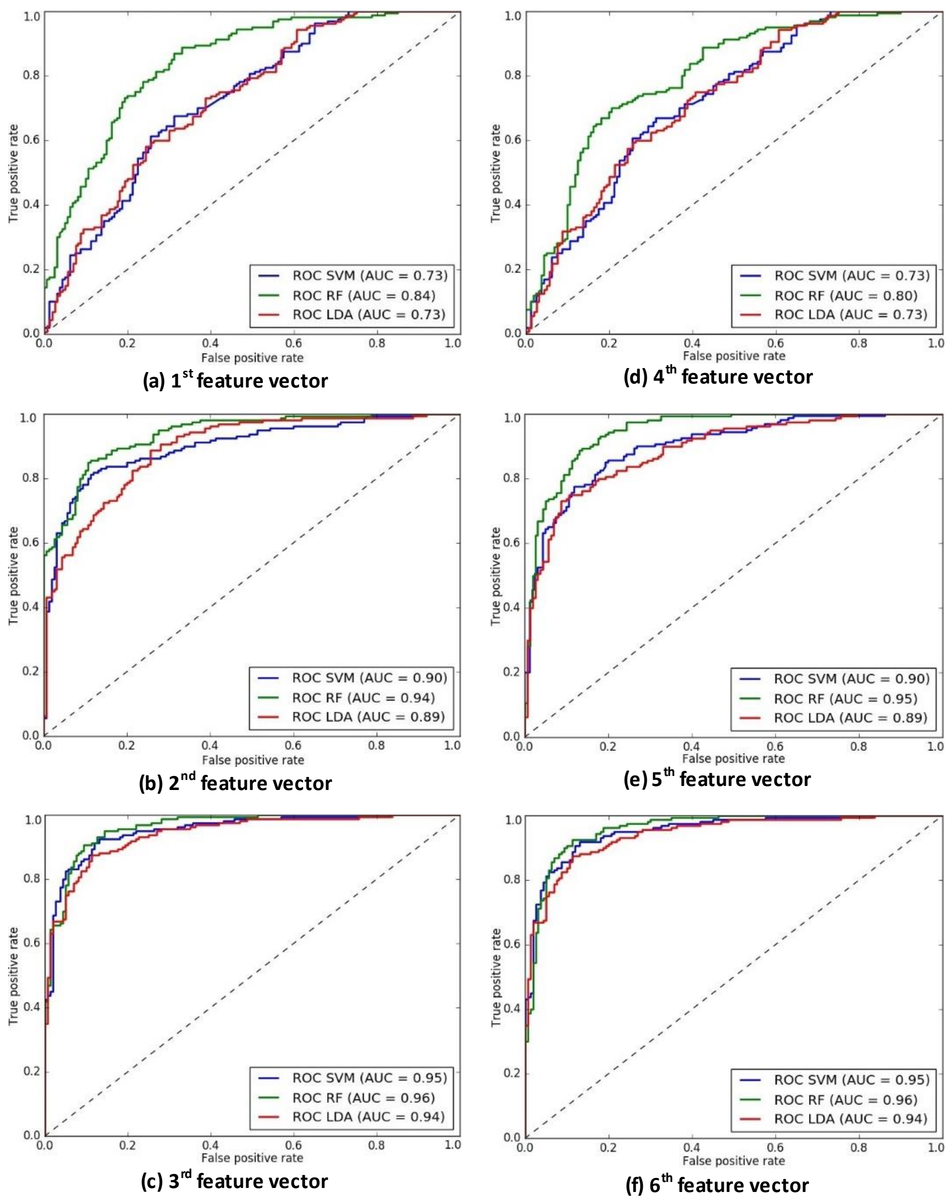


**Figure 5.** ROC curves classification results of SVM in blue, RF in green and LDA in red using different feature vector configurations. (a-c) feature configurations which include unfused material; (d-f) feature configurations which do not include unfused material. Higher AUC values mean better performance.

RF and LDA supervised learning algorithms. Chars were classified as "high reactive" and "low reactive" particles. Ten morphological features including ICCP classification characteristics were used to build the classifiers: area, unfused material, number of pores, porosity, wall thickness (the first, second and third quartiles), sphericity, roundness, compactness, solidity and defect area.

Results showed that the unfused material is not the most useful characteristic to begin classification for chars from Cundinamarca coal, since Cundinamarca coal contains low quantities of the inertinite maceral. As a consequence, this coal produces low quantities of unfused material in the char. This led to low accuracy values using the ICCP decision tree.

On the other hand, supervised learning algorithms allow to build robust and precise char classification models for Cundinamarca coals. The models trained with the four ICCP features — unfused material, porosity, sphericity and second quartile of wall thickness— improved the accuracy obtained following the ICCP decision tree with a maximum difference of 0.1782 using RF. Furthermore, considering related morphological features, such as compactness, solidity, defect area and roundness measurements exhibit a higher accuracy —it is observed for RF a maximum improvement of 0.3038 with respect to the ICCP decision tree.

Although SVM, RF and LDA classifiers have a similar classification performance, RF showed higher accuracy values. The best accuracy of 0.8731 was obtained with the ten morphological features.

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## 7 DISCLOSURE STATEMENT

NO potential conflict of interest was reported by the authors.

## 8 NOTES ON CONTRIBUTORS

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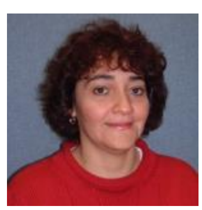

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