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A new Model for Predicting Spontaneous Combustion of Coal Potential based on Decision Tree

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Abstract

One of the most prevalent risks in coal mines is spontaneous combustion (spon com) of coal, which is a major source of coal loss in these environments. Therefore, to avoid coal loss and preventing the potential risks, a criterion for predicting the spon com of coal is essential. The main purpose of this work is to present a new model for predicting the spon com of coal potential using a decision tree technique, known as the Spon com of coal decision Tree (SCCDT). In this research work, after identifying the effectiveness of each parameter on the spon com of coal, several parameters were examined, including characteristics such as moisture, ash, pyrite, volatile matter, fixed carbon, mineralogy, and petrography. Subsequently, the primary phases of applying the decision tree model were analyzed, and the probability of the spon com of coal potential was determined based on intrinsic parameters. Finally, the mentioned parameters were categorized, and an appropriate model for classifying the spon com of coal potential was developed. In the SCCDT model, the spon com of coal potential was divided into three classes: low, medium, and high. The model was then applied to Parvadeh I to IV coal mines in Tabas. A comparison of the study's findings showed relatively good agreement with the SCCDT model. Using the proposed model can help to predict the spon com hazard and prevent the various life-threatening/mortal and financial risks.

1. Introduction

Coal, as one of the fossil fuels, is a combustible material. Due to the nature of coal, underground coal mining creates challenging working conditions and various hazards that need to be identified and addressed from the early stages of mine design and extraction planning through continuous mine monitoring. Strategies for predicting, preventing, and controlling these hazards should also be established. Some of the main hazards in underground coal mines include the collapse of advance tunnels, coal gas explosions, coal spontaneous combustion (spon com), subsidence, and rock burst. The spon com of coal is a highly complex physicochemical process that can contribute significantly to mine fires. Understanding the spon com of coal phenomenon in mines is a difficult task. To avoid such an event and the related environmental hazards, this process and its influencing parameters must be thoroughly examined [1-6].

One of the most prominent causes of mine fires is the occurrence of the spon com of coal. It can occur due to oxidation at various ambient temperatures up to the ignition temperature of coal, even without an external heat source (Figure 1) [7].

The spon com of coal is an exothermic process in which the coal oxidation leads to an increase in its temperature. This temperature rise is caused by a change in the intrinsic thermal characteristics of the material, which in some cases results in fires and combustion (Figure 2) [8].

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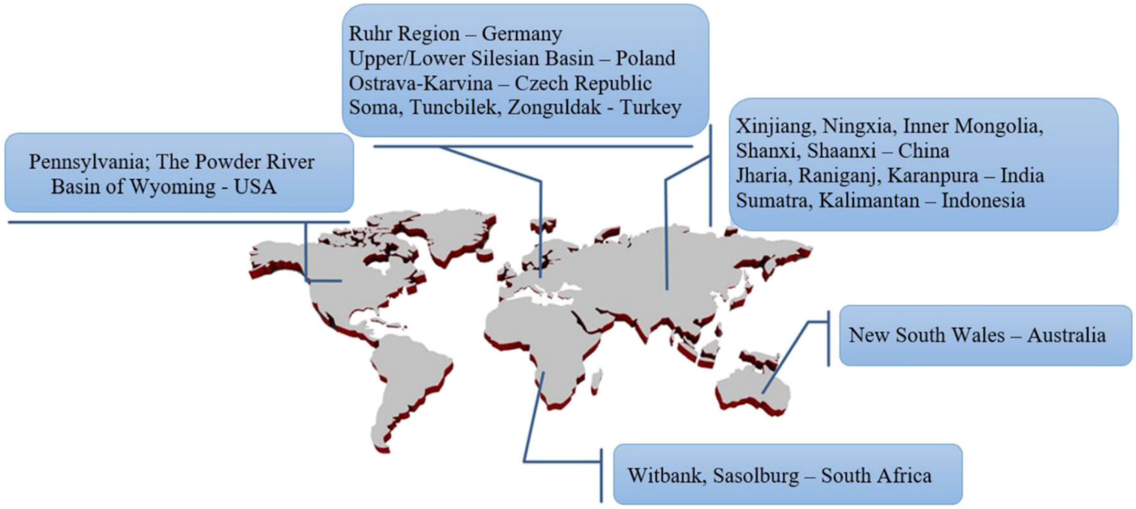

Figure 1. Countries and fire zones that have experienced spon com problems [7].

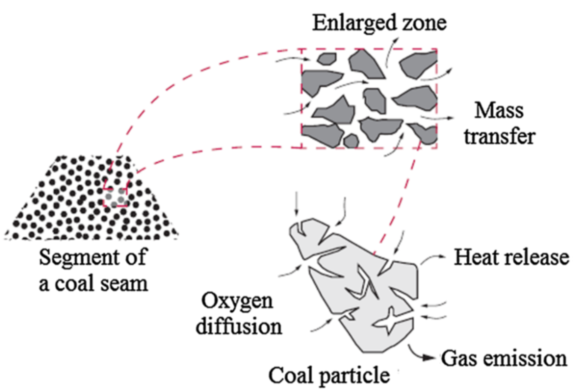

Figure 2. Fundamental phenomena occurring in coal oxidation process [8]**.**

The consequences of the spon com of coal include fatalities among personnel, psychological distress among surviving personnel, environmental pollution, loss of mining equipment and facilities, interruptions in mining production, mine closures; etc. [9].

However; coal is present. The process of the spon com of coal can potentially begin. One of the strategies for continuous monitoring of the spon com is risk assessment of this phenomenon in locations such as underground mines, open-pit coal mines, abandoned coal mines, coal dumping sites, waste dumps, and during coal transport, particularly when shipped by sea [9].

Due to the constant presence of safety, economic, and environmental risks, the risk assessment of the spon com of coal must be conducted at every stage of mine design, operation, closure, and reclamation [10-12].

For risk analysis, the first step is to assess the spon com of coal potential, and to identify the influencing parameters on this phenomenon. Numerous parameters affect this process, which fall into three groups: intrinsic characteristics, mining characteristics, and geological characteristics. Key parameters within the intrinsic characteristics category affecting the spon com include pyrite, ash, and moisture levels, coalification levels, volatile matter, and petrography. Each of these influencing parameters exerts either an increasing or decreasing effect on the spon com of coal.

To better understand the spon com of coal, it is vital to determine the influence of each of the effective parameters on this process. The optimal method for examining the spon com of coal potential is one that employs a large set of input data to assure reliability, with minimal error. Additionally, this method should be practical for easy use throughout the entire mining operation.

Until now, many studies have been carried out on the influence of various parameters in the development of the spon com of coal. However, to date, no model has been developed that incorporates four essential elements: a large amount of input data, applicability to various mines, minimal error, and ease of use. Given these considerations, research in this area appears essential. Therefore, based on an analysis of earlier research and observations related to the spon com of coal, the significant influencing parameters were identified and collected for this study. Subsequently, efforts were made to develop a new model based on the identified needs. The aim was to develop a high-performance model for evaluating the spon com of coal potential in underground coal mines, particularly those employing the longwall mining method.

Gathering a large amount of data to make sure the developed model would be comprehensive and adaptable to different mines was a crucial first step towards accomplishing the objective of this study. The next phase involved employing a method with very low practical error, which ultimately led to the development of the model based on the decision tree method.

Based on the characteristics of the coal, a mining expert can use the decision tree to determine the level of the spon com of coal potential. A range of methods including laboratory and system-based methodologies are available to assess the spon com of coal potential. One of the most recent methods used to measure this potential is the Crossing Point Temperature (CPT) method, which is a laboratory-based approach. Table 1 provides a classification of CPT values and the corresponding spon com of coal potential [13].

Table 1. Classification of CPT values and the status of spon com of coal potential [13]

Class	CPT value (Celsius)	The spon com of coal potential
1	>160	low
2	140-160	medium
3	120-140	high

Finally, a novel model based on the decision tree method has been developed to accomplish the main goal of this study. It includes influencing parameters on spon com potential and uses CPT values as the criterion for assessing this potential.

During the model development process, a set of data was used for training the model, and another set of data was retained for testing. Ultimately, to validate the model, the characteristics of a real mine were implemented to assess its performance. For model training, an intelligent neural network method was employed to determine the importance of each parameter and its influence on the spon com of coal potential.

The objective of this study is to use the intrinsic characteristics of coal to assess its spon com potential and classify it according to CPT, which will serve as a decision-making and practical criterion for mine managers.

2. Literature Review

Over the last century, many studies have been conducted on the coal spon com. The first study on pyrite oxidation was carried out by Parr and Hilgard in 1925 [14]. Under the influence of various parameters, different types of coal with varying compositions may undergo spon com [15]. If this occurs, the safety, economy, and surrounding environment of the mines will be at risk, and a significant quantity of coal resources will be lost [16]. Determining the potential of coal spon com based on its composition is crucial, and studies on this subject continue throughout the entire mining life cycle and even beyond [17]. In the following, the background of the study is presented.

In the past two decades, comprehensive studies have been conducted on the potential of coal spon com, along with its characteristics, in various mining locations including underground spaces, open-pit mines, and coal stockpiles [18, 19]. Furthermore, relations have been established to determine the correlation between the parameters influencing the potential of coal spon com and its characteristics [20]. In one study, parameters influencing the spon com of coal seams were identified, and some studies offered a risk assessment system for spon com based on historical data from Chinese mines and hierarchical analytic methodologies [10].

In another study, comprehensive analyses on coal mine fires in recent decades, their environmental impacts, methods for preventing the spon com of coal, and classification systems for assessing the risk of coal spon com were presented [5, 21, 22]. One approach to prevent the spon com of coal was accurate prediction of this phenomenon, with one study using a random forest methodology to forecast the potential of coal spon com [23]. According to the studies, coal moisture, as one of its intrinsic characteristics, plays a crucial role in determining its spon com potential; in one study, the effects of moisture and intrinsic characteristics of coal on its spon com potential were analyzed [24]. A comprehensive study was conducted to examine the spon com of coal potential, which revealed that an increase in fixed carbon, moisture, hydrogen, volatile matter, nitrogen, and pyrite, as well as a decrease in ash content, enhances the spon com of coal potential [25].

Another study provided a comprehensive review of academic and industrial research on the spon com of coal potential, offering various methods for measuring this potential, including mathematical, laboratory, and probabilistic approaches [26]. A study developed an artificial intelligence model for predicting the spon com of coal potential using approximate analyses [27]. Additionally, a model for predicting coal spon com was developed using hybrid simulation and support vector machines [28].

In one study, the tendency for coal spon com was calculated using MLP and RF methods for 204 coal samples, where the RF method demonstrated better performance compared to the MLP method. Machine learning was proposed as a novel approach for predicting the tendency of coal spon com [29].

Mishra et al. also presented a classification system for coal seams based on self-heating using an Internet of Things framework. In this work, the intrinsic characteristics of coal samples were used as system inputs [30].

Mustafa et al. (2024) predicted the risk level of the spon com of coal using the FTA (Fault Tree Analysis) method [31]. Table 2 shows research over the past century that focusses on various elements of coal, such as its intrinsic characteristics, geological features of coal seams, and mining characteristics, all of which are crucial for predicting the spon com of coal potential.

Table. 2. The study of the parameters affecting coal spon com in different researches.

No.	Reference	Year	Intrinsic characteristics						Geological characteristics				Mining characteristics		
			FC	AC	MoC	PC	VM	MC	GC	DOS	DAS	TOS	VS	AR	ER
1	Ashutosh Mishra[30]	2024		√	√		√								
2	Caiping Wang[32]	2023	√	√	√		√								
3	Xuefeng Xu[33]	2023	√	√	√		√								
4	Nilufer Kursunoglu[34]	2022							√				√		
5	Xiaodong Zhou[35]	2022							√						
6	Saffari[36]	2022				√		√							
7	Ashish Kumar Ghosh[37]	2022	√	√	√		√								
8	Khadija Omar Said [27]	2021	√	√	√		√								
9	Jun Zeng [38]	2021			√										
10	Li Shen [39]	2021	√	√	√		√								
11	Jun Deng[28]	2021							√						
12	A. R. Gbadamosi [40]	2021	√	√	√		√								
13	Hao Shao [41]	2021											√		
14	Moshood Onifade [42]	2020	√	√	√		√								
15	Yutao Zhang [43]	2020	√	√	√		√								
16	Saffari [44]	2020						√							
17	Saffari [45]	2020						√							
18	Yuguo Wu [46]	2020			√										
19	Magdalena Tutak [47]	2020											√		
20	Marek Wieckowski [48]	2020	√	√	√		√								

After examining previous studies and collecting and analyzing data, it was found that numerous parameters significantly affect the spon com of coal potential, although most articles have limited themselves to examining a limited number of these parameters. Another noteworthy point is the total number of samples studied, which was not very most in previous articles, and the models presented are not applicable to other coal regions. As presented in Table 2, the parameters influencing the spon com of coal were categorized into three groups: intrinsic characteristics, geological characteristics, and mining characteristics. Moisture, ash content, volatile matter, fixed carbon, pyrite, and petrographic composition are the intrinsic parameters impacting coal spon com that this study focusses on. Additionally, in the current research, the training and test data are collected from the previous studies (according to Table 2). Also, the highlighted sections in Table 2 are the researches that assessed the intrinsic, mining and geological characteristics, simultaneously.

To assess the spon com of coal potential, in this study, the values from the CPT method were used as an indicator of its tendency for spon com. Additionally, as outlined in Table 2, these values were employed as the output parameter, and the new model's error was determined accordingly.

In the subsequent sections, the methodology, model implementation, model validation, discussion, and conclusions are described, which detail the data collection and analysis, model implementation and development, prediction of the spon com of coal potential, and its applications.

Table. 2. The study of the parameters affecting coal spon com in different researches (continued).

No.	Reference	Year	Intrinsic characteristics						Geological characteristics			Mining characteristics		
			FC	AC	MoC	PC	VM	MC	GC	DOS	DAS	TOS	VS	AR	ER
21	Li Ma[49]	2020	√	√	√		√								
22	N. K. Mohalik [50]	2020						√							
23	Jiuyuan Fan [51]	2019	√	√	√		√								
24	Dmitry Dmitrievich Golubev [52]	2019										√			
25	Saffari [53]	2019			√	√									
26	Saffari [54]	2019						√							
27	Saffari [55]	2019						√							
28	Saffari [56]	2019						√							
29	Fuqiang Yang [57]	2019				√									
30	Sergey Meshkov [58]	2019											√		
31	Amir Saffari [59]	2019	√	√	√	√	√	√							
32	Xiaowei Zhai [60]	2019							√				√		
33	Moshood Onifade [61]	2018	√	√	√	√	√								
34	Zhang [62]	2018			√										
35	Liu [63]	2017											√	√	√
36	Zhao [64]	2016			√										
37	Hetao [65]	2016									√		√		
38	Xia [66]	2015											√	√	
39	Panigrahi [67]	2014			√										
40	Sahu [68]	2013		√	√		√								
41	Liming [69]	2012											√		
42	Taraba [70]	2011												√	
43	Beamish [71]	2010			√										
44	Bo-tao [72]	2009												√	
45	Beamish [73]	2008		√											
46	Mitchel [74]	2003											√		
47	Cotterell [75]	1997						√							
48	Ramlu [76]	1991							√						
49	Chandra [77]	1990				√	√								
50	Hodges [78]	1963			√										
51	Parr [14]	1925				√									

3. Methodology

Machine learning algorithms are widely used in classification and prediction tasks. One of the earliest classification approaches is the decision tree, which uses decision-making rules to combine a hierarchical model with features to generate a tree-like classification model.

This method is appropriate for exploration data analysis and predictive modelling applications. The algorithms used to construct decision trees were first introduced by Hunt in 1966 [79]. The ID3 and CART algorithms were subsequently introduced in 1980 and 1984, respectively. It is noteworthy that these algorithms have influenced the development of other algorithms. Most decision tree learning algorithms operate based on a greedy top-down search within the space of existing trees [80, 81].

Decision trees can be used to discover features and extract patterns in large databases, making them highly efficient for decision-making and predictive modelling.

The analysis in classifications generated by decision trees is flexible. Additional advantages of this method include the ability to uncover unknown relationships, suitability for analyzing large datasets in a short amount of time, the feasibility of model evaluation using statistical methods, and the minimal need for data preparation steps.

The disadvantages of decision trees include the limited availability of training samples, the high cost of tree pruning, unsuitability for estimating functions with continuous values, the increased likelihood of error when the number of categories is high, and the significant computational cost of generating a decision tree [82-84].

In this study, to predict the spon com of coal potential, a model was developed based on decision tree. This study consists of five main steps, as illustrated in Figure 3, which are detailed in the parts that follow.

3.1. Step 1: Review of studies

In the first step, all available studies on predicting the spon com of coal potential were thoroughly reviewed. As a result, eight intrinsic characteristics of coal including moisture, ash content, volatile matter, fixed carbon, pyrite, and petrographic composition (proximate analysis results), as well as CPT (Critical Point Temperature) values, were identified and recorded.

3.2 Step 2: Data preprocessing

The second phase was data preprocessing, which included statistical analysis of the 165 data points obtained from the previous step as well as a description of the researched data. This step involved examining and analyzing the relationships between the database's input and output data.

3.3. Step 3: Data processing

For data processing, as shown in Figure 3, the initial phase involved converting continuous input data into discrete data and forming a discrete input matrix. To construct the decision tree hierarchically, the procedure followed the Function 1.

$$TDT(D) \rightarrow T \quad (1)$$

In each phase of calculating Function 1, all input data were analyzed, and the factor with the greatest effect over the data was selected. Finally, after completing the phases of Step 3, the new SCCDT model, or developed tree, was constructed.

3.4. Step 4: Model evaluation

In this step, the proposed model was evaluated using database data, and model validation was performed with data from the stopes of Parvadeh Tabas coal mine. This allowed for a comparison of the classification results obtained using the SCCDT model with field experiences, thereby demonstrating the efficacy of the new developed model.

3.5. Step 5: using the decision tree

Finally, in the Tabas coal mine, coal stopes with varying spon com potentials were identified, and the findings were used to improve the mine safety.

4. Model Implementation

In this section, the six main steps of the new model for predicting the coal spon com and evaluating its potential were carried out in the order shown below.

4.1. Step 1: identification of influential parameters

The initial step towards reaching the purpose of study was to properly determine the characteristics impacting the coal spon com. Therefore, as outlined in Table 3, factors influencing the spon com of coal potential were determined and investigated including intrinsic characteristics, geological characteristics, and mining characteristics of coal.

Table 3. Distribution of studies on the spon com of coal potential from 1980 to the present.

Characteristics affecting the spon com of coal potential	Number of studies
Intrinsic characteristics	32
Geological characteristics	2
Mining characteristics of coal	12

As indicated in Table 3 and the literature review section, the intrinsic characteristics of coal hold greater importance compared to the other two characteristics in spon com. Therefore, this study focused on the parameters related to intrinsic characteristics.

4.2. Step 2: Database

In the next step, to evaluate the coal's tendency for spon com, the intrinsic characteristics of coal were analyzed in order to establish a relationship between these characteristics and the CPT values. As a result, a total of 165 data points were collected from various studies on different underground coal mines. In all studies, proximate analysis was used to assess the contents of moisture, ash, volatile matter, and fixed carbon (according to the standards of the American Society for Testing and Materials (ASTM)).

Table 4 shows the findings of proximate analysis, petrographic maceral analysis, and the CPT values of the coal data. Figure 3 depicts the frequency distribution, and the last column contains the results of the CPT tests. As can be observed, among the 165 samples, the minimum CPT value was around 70, the maximum CPT value was 200, the average CPT was 153, the first quartile was 140, and the third quartile was 174.

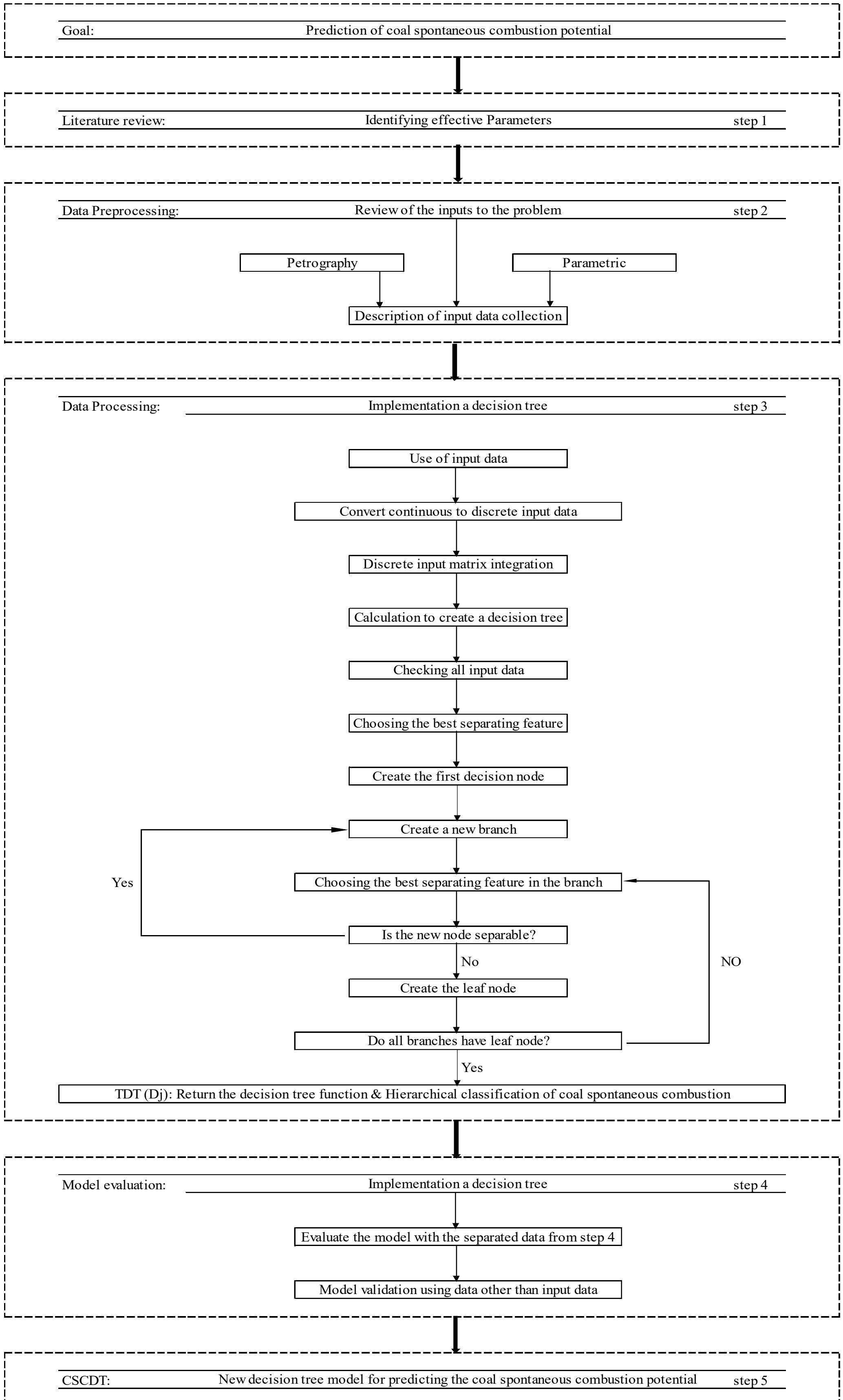

Figure 3. Main stages of the current study.

Table 4. Results of proximate analysis, petrographic maceral analysis, and CPT values of coal data.

Statistical Variable	CPT	Intrinsic characteristics- %							
		Inertinite	Liptinite	Vitrinite	Pyrite	Fixed carbon	Volatile matter	Ash	Moisture
Mean	153	36.48%	7.61%	55.91%	2.00%	43.97%	23.32%	25.61%	5.11%
Median	149	35.33%	7.93%	57.37%	1.75%	44.25%	23.20%	23.01%	3.22%
Mode	180	0.00%	11.49%	72.08%	0.00%	38.09%	18.50%	41.18%	2.24%
Standard deviation	26.6	21.08%	4.03%	18.21%	1.85%	11.14%	6.45%	13.94%	5.34%
Sample variance	714	4.47%	0.16%	3.34%	0.03%	1.25%	0.42%	1.96%	0.29%
Range of variation	131	90%	17%	84%	12%	60%	42%	77%	31%
The minimum value	68.9	0.00%	0.60%	2.40%	0.00%	7.47%	2.00%	2.20%	0.47%
The maximum value	200	90.40%	17.86%	86.62%	12.13%	67.40%	43.98%	79.25%	31.85%
the first quartile	140	24.54%	4.18%	47.06%	0.50%	38.05%	18.50%	15.25%	1.98%
the third quartile	174	48.75%	9.58%	65.23%	2.70%	51.55%	27.95%	32.53%	6.27%
Number of values	165	165	165	165	165	165	165	165	165

According to the CPT frequency distribution chart, 31 samples exhibit high spon com potential, 86 display moderate spon com potential, and 48 have low spon com potential (Figure 4).

4.3. Step 3: Database description

Table 4 presents the results of the proximate analysis and petrographic maceral analysis. The means, standard deviations, first quartiles, and third quartiles for the eight main parameters are provided.

Figure 5 shows the frequency distribution of coal samples. As observed, the total number of samples was 165.

In this section, about 25 of the 165 samples were randomly selected for model evaluation. Additionally, data from the Tabas mine was used for model validation.

4.4. Step 4: Relationship between the proximate analysis values of intrinsic properties and the experimental CPT values.

For each of the intrinsic characteristics, both linear and nonlinear regression analyses were conducted (Figure 6). Finally, the model with the highest R2 value was selected for further investigation and analysis in this study.

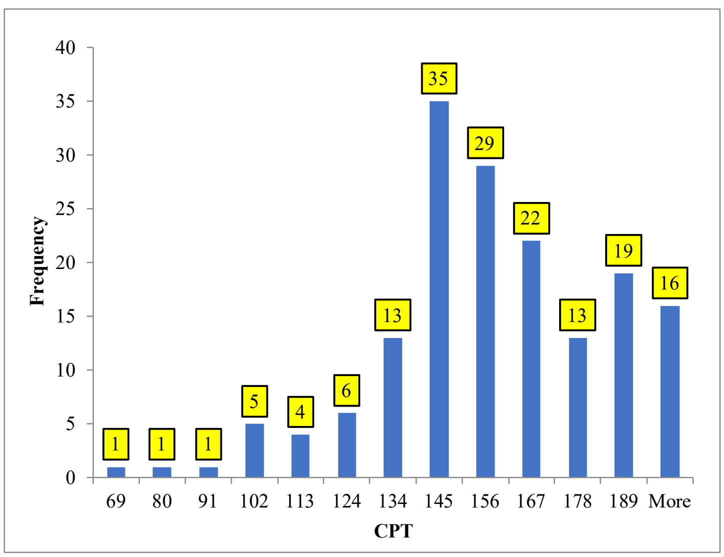

Figure 4. Frequency distribution chart of CPT values.

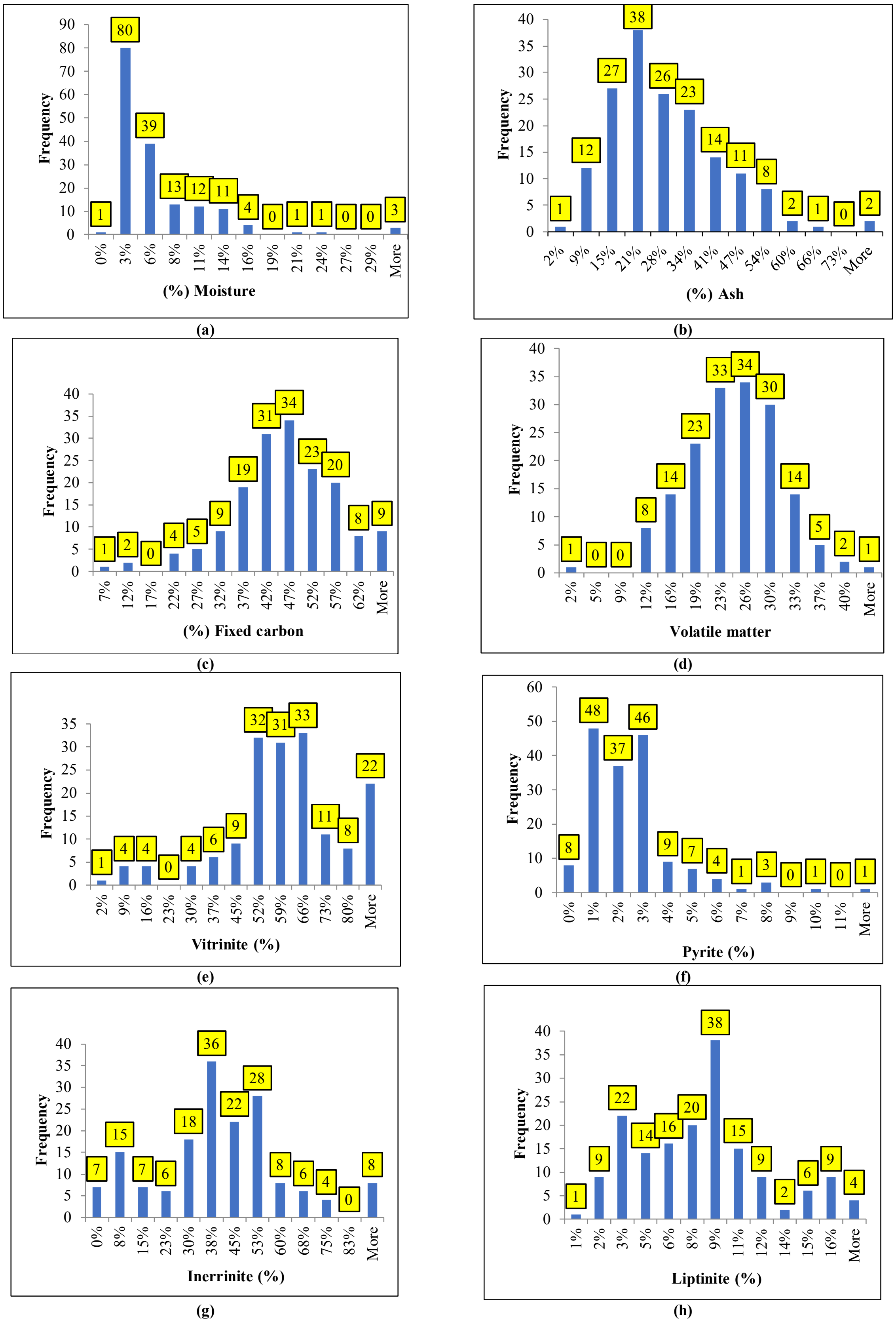

Figure 5. Frequency distribution chart of intrinsic characteristics values of coal.

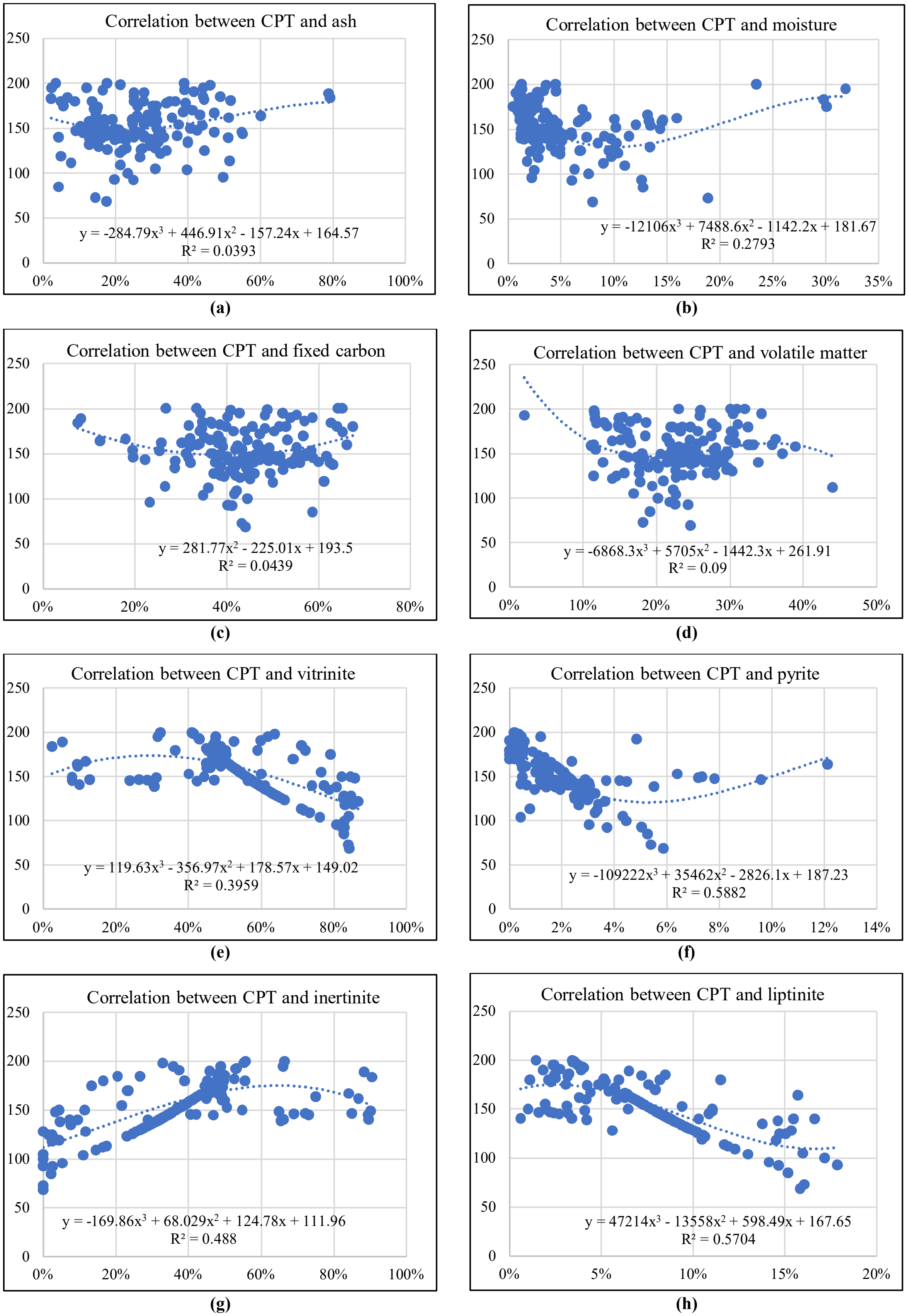

Figure 6. Chart of the relations between intrinsic characteristics values and CPT values.

The findings showed that the R2 value of Figure 6a to 6h were 0.039, 0.279, 0.044, 0.09, 0.395, 0.588, 0.488, and 0.570, respectively. The results also indicated that when conducting a univariate analysis of each parameter in relation to the CPT values, the highest R-squared correlation (R2) was associated with pyrite, with a value of approximately 0.59, while the lowest R2 were related to ash and fixed carbon, with values around 0.04. As demonstrated in Figure 6, none of the intrinsic characteristics exhibited a direct or indirect linear relation, and their R2 values were not very high.

Therefore, to gain a deeper understanding of the relations between the intrinsic characteristics of coal and the CPT values, decision tree method was used in the main step of processing.

4. 5. Step 5: Conversion of continuous input data to discrete data

The third phase, as indicated in Figure 3, began with the conversion of continuous input data into discrete data and the formation of a discrete input matrix. For this conversion, the first quartile, mean, and third quartile values of each intrinsic parameter were utilized. In this algorithm, a decision tree was constructed for each sample of the input data, which hierarchically included decision nodes and leaf nodes.

4.6. Step 6: Classifier selection

After reviewing all the input data, the best classifier feature and the factor with the greatest impact among the data were selected. The pyrite parameter emerged as the first decision node at the highest level of the tree, with a value of 64.0%, resulting in two branches. At the second level of the tree, the inertinite parameter, with a value of 12.36%, was the determining factor. Based on these two levels, if a coal sample contains less than 64.0% pyrite and more than 12.36% inertinite, the probability that the coal sample has weak spon com potential is approximately 97%.

Similarly, if the pyrite content is greater than 64.0% and the inertinite content is greater than 31.758%, the probability that the studied coal sample has a moderate spon com potential is approximately 74%.

On the other hand, if the pyrite content is greater than 64.0% and the inertinite content is less than 31.758%, the probability that the studied coal sample has a high spon com potential is approximately 82%.

Finally, upon completing the five steps of the new developed model, the final decision tree was obtained, as shown in Figure 7.

5. Model Validation

The fourth step in Figure 3 aims to evaluate and validate the new proposed model, which is conducted in two ways due to the importance of the coal spon com. The model evaluation was performed on a subset of the data put aside in Step 3. For this, of the 25 sample cases used in the decision tree to predict spon com potential, 23 were properly predicted, with only two prediction errors.

For the validation of the new model, data from the stopes of Parvadeh Tabas coal mine were utilized.

The Parvadeh underground coal mines are located 85 km southeast of Tabas, in South Khorasan Province, Central Iran. The Tabas coal mines, with an estimated reserve of 1.2 billion tons, are among the most important coal mines in Iran. The Parvadeh coal mines consist of six zones, which are divided based on the main faults (Figure 8). These mines contain five coal seams named B1, C1, B2, C2, and D. Among these seams, only the B and C seams are suitable for extraction in terms of quality and quantity. Table 5 presents the characteristics of the intrinsic parameters for 9 coal samples from 4 Parvadeh Tabas mines, which were used to validate the proposed model.

The results of the experimental and predicted CPT values are presented in Table 6. As can be seen, all nine Tabas coal samples were predicted properly.

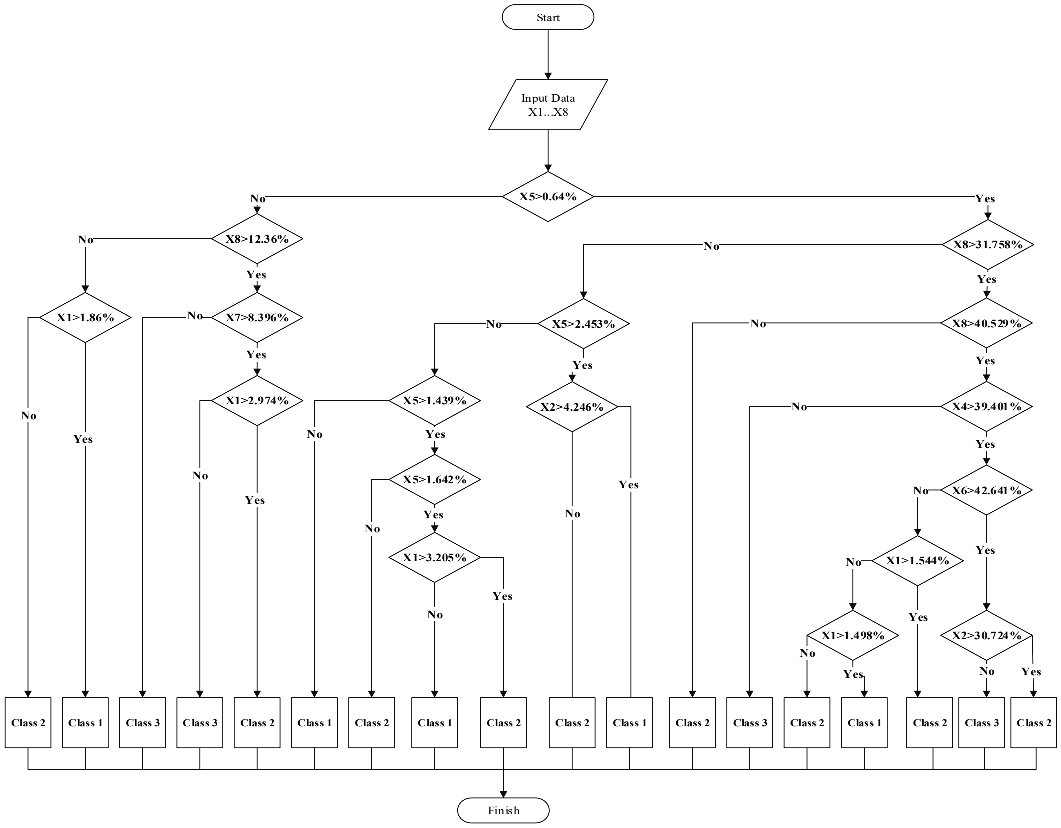

Figure 7. Developed model of SCCDT.

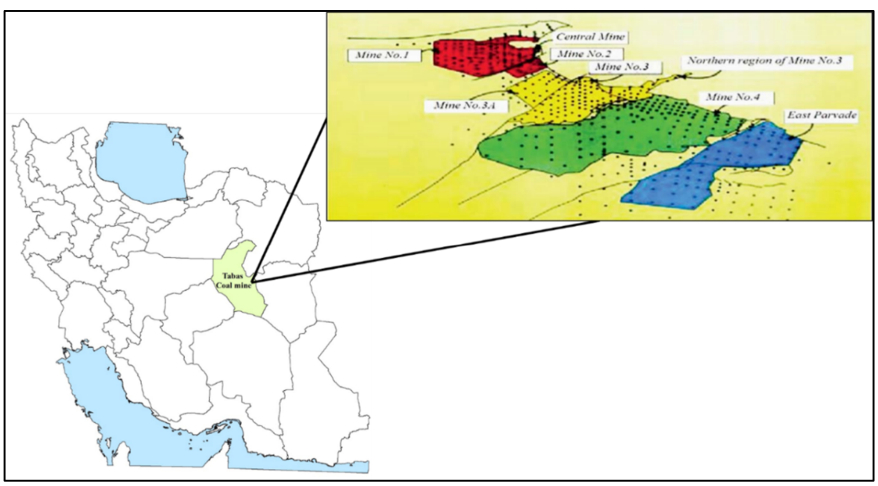

Figure 8. Location of the Parvadeh coal mines and the separating faults.

Table 5. Intrinsic parameters of 9 coal samples from 4 Parvadeh Tabas mines.

sample code	moisture (%)	ash (%)	volatile matter (%)	fixed carbon (%)	pyrite (%)	vitrinite (%)	liptinite (%)	inertinite (%)	class of tendency to spon com
$S_1P_1C_1W_3$	0.768	27.932	17.383	53.917	0.11	47.31	3.89	48.69	1
$S_2P_1C_1E_3$	2.739	36.588	14.936	45.737	0.45	36.17	8.15	55.23	1
$S_3P_2B_1B_2$	4.68	33.107	14.969	44.244	1.78	46.22	10.69	41.31	2
$S_4P_2B_1B_3$	6.556	32.301	17.645	43.498	4.52	80.23	15.25	0	3
$S_5P_2B_2B_3$	3.732	43.951	15.379	36.938	1.53	44.73	5.8	47.94	1
$S_6P_3C_1B_1$	7.94	24.386	21.113	46.561	4.66	78.97	16.37	0	3
$S_7P_4C_1B_1$	2.56	15.114	23.114	59.212	1.51	39.44	9.25	49.8	2
$S_8P_4B_2B_4$	0.866	17.594	24.49	55.99	1.06	39	14	47	2
$S_9P_4C_1B_4$	1.565	19.765	25.04	52.26	1.37	39	12	49	3

Table 6. Results of experimental and predicted CPT values from 4 Parvadeh Tabas mines.

Name	The class of tendency to spon com based on the experimental CPT value	The class of tendency to spon com based on the predicted CPT value
$S_1P_1C_1W_3$	weak	weak
$S_2P_1C_1E_3$	weak	weak
$S_3P_2B_1B_2$	moderate	moderate
$S_4P_2B_1B_3$	high	high
$S_5P_2B_2B_3$	weak	weak
$S_6P_3C_1B_1$	high	high
$S_7P_4C_1B_1$	moderate	moderate
$S_8P_4B_2B_4$	moderate	moderate
$S_9P_4C_1B_4$	high	high

6. Discussion

This work proposed a new model for predicting spon com potential based on decision tree, developed through the collection of a database from the review of all relevant studies on the coal spon com. In this work, the main stages have been carried out in 5 steps including review of studies, data gathering and preprocessing, implementation of decision tree by data processing, model evaluation and model presentation.

The implementation of the decision tree model has also been carried out in 6 steps including identification of influential parameters on spon con potential, database, database description, examination of correlation between input and output data, conversion of continuous input data to discrete and classifier selection.

The database has been collected by studying all the articles related to spon com. It is worth noting that the new decision tree model presented for predicting spon com potential of coal has been presented for the first time by the authors of this article, which is one of the innovations of this article.

The model was finally validated using data from the Table coal mines. The results indicated that the C1 coal seam in Parvadeh 1 and the B2 seam in Parvadeh 2 exhibit weak spon com potential. Additionally, the C1 seams in Parvadeh 2 and 4, as well as the B2 seam in Parvadeh 4, show moderate spon com potential. The B1 seam in Parvadeh 2, the C1 seam in Parvadeh 3, and the C1 seam in Parvadeh 4 demonstrate high spon com potential.

Given the statistical analysis results and the complexity of predicting the spon com of coal potential, it cannot be expected to have accurate linear relations. Therefore, through statistical analysis, as shown in the Figure 6 (CPT Regression with parameters), the regression between the intrinsic characteristics and the CPT value was studied nonlinearly, with R-squared correlation (R2) ranging from 0.04 to 0.6. The R-squared correlation (R2) for eight parameters were determined.

As mentioned, pyrite and liptinite have the greatest coefficients of determination in this nonlinear regression when compared to the other intrinsic characteristics. Considering the R-squared correlation (R2) for the parameters, it is not possible to predict the spon com of coal potential using a single parameter; instead, a combination of parameters should be employed for this prediction. Consequently, in the decision tree created, pyrite was of high importance at the highest level (the first decision node) and served as the primary classifier factor, while the second factor was inertinite. However, in the nonlinear regression, the R-squared correlation (R2) for liptinite was greater than that for inertinite.

Ultimately, a new model, SCCDT, was proposed in this study. In the evaluation phase of the SCCDT model, the error rate of the decision tree was approximately 8% (after setting aside 25 sample cases). During the validation phase of the SCCDT model, coal samples from Parvadeh Tabas were used, and all were properly predicted. Samples 4, 6, and 9 exhibited high spon com potential. Through the two phases of evaluation and validation, it was demonstrated that the proposed SCCDT model is reliable.

7. Conclusions

Coal exhibits varying spon com properties influenced by factors such as intrinsic, geological, and mining characteristics. Given the importance of intrinsic characteristics over the other two characteristics and to better understand the spon com of coal potential, this study proposed a new model for predicting spon com potential based on decision tree, which was developed by collecting a database from a review of all relevant studies on the coal spon com.

In this study, the findings from the new proposed SCCDT model indicated that the trained decision tree had an error rate of about 8% after putting aside 25 sample instances. When applying the decision tree to the coal samples from Parvadeh Tabas, all samples were properly predicted. Samples 4, 6, and 9 exhibited high spon com potential. The evaluation and validation of the model also demonstrated that the suggested SCCDT model is reliable, and this new model can be used to predict the spon com of coal potential with extremely low error.

The current study indicated that, despite the complexity of the coal spon com phenomenon, a hierarchical classification approach can be effectively used to predict the spon com of coal potential in various mines. Finally, it is suggested for future research that the coal spon com potential be investigated using other intelligent methods or nonlinear functions and compared with the model presented in this article.

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دانشگاه صنعتی شاهرود

مدلی جدید برای پیش‌بینی قابلیت خودسوزی زغالسنگ براساس درخت تصمیم

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کلمات کلیدی

مدلسازی فرکتالی

غلظت-فاصله از گسل

غلظت-حجم

تعداد-اندازه، نفوذپذیری

چکیده

یک کار مهم برای مدل‌سازی مخازن دارای ساختارهای زمین‌شناسی و توسعه میادین نفتی، تعیین ویژگی‌های ژئومکانیکی مانند نفوذپذیری است. هدف اصلی این پژوهش، شناسایی پهنه های نفوذپذیری در مخزن آسماری میدان نفتی گچساران (جنوب غرب ایران) بر اساس داده های هرزروی گل می باشد. هرزروی گل به روش کریجینگ معمولی به صورت سه بعدی برآورد شد. سپس مدل‌های فراکتالی تعداد-اندازه، غلظت-حجم و غلظت-فاصله تا گسل برای طبقه‌بندی پهنه‌های نفوذپذیری استفاده شد. مدل فراکتال غلظت-فاصله تا گسل سه پهنه نفوذپذیری را نشان می‌دهد و مدل‌سازی فراکتال غلظت-حجم هشت پهنه را با رفتار چندفرکتالی شاخص نشان می‌دهد. علاوه بر این، تجزیه و تحلیل فراکتالی با روش تعداد-اندازه نشان داد که یک رفتار چندفراکتالی با پنج پهنه است. همبستگی بین نتایج به‌دست‌آمده از این روش‌های فراکتالی نشان می‌دهد که پهنه‌های به‌دست‌آمده دارای همپوشانی مناسبی با هم هستند. مناطق نفوذپذیری با ارزش بالا بر اساس مدل‌های فراکتال غلظت-فاصله تا گسل و غلظت-حجم از هرزروی گل ۵۰۱ بشکه در روز و ۶۳۰ بشکه در روز با مدل‌سازی تعداد-اندازه شروع می‌شوند. مدل‌سازی فراکتالی نشان می‌دهد که پهنه‌های با نفوذپذیری بالا در بخش‌های جنوب غربی، شمال غربی و جنوبی میدان نفتی گچساران وجود دارد که می‌تواند بخش شکسته سنگ مخزن آسماری باشد. گسل های اصلی از این میدان نفتی با مناطق نفوذپذیری به دست آمده از طریق مدل سازی فراکتال در ارتباط است.

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