ADAPTIVE COAL CLASSIFICATION USING DEEP LEARNING

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Abstract—The first effort in learning about coal is observing coal features. This project developed a coal search system that allows users to do a search even when they do not know the coal names imply by observing coal characteristics. At present, coal classification uses machine vision to extract and analyze color, size, shape, and surface texture. Still, the new extraction margin method can be carried out roughly yet there is still a difference between the margin of extracted polygon, shape and the margin of the shape of original image. The project aims in finding the gangue in the coal. Total gangue percent in the coal data is then calculated and displayed which is based on pixels count of gangue colors. This assists in evaluating the coal quality. If future researchers were to expand to other features, coal gangue, etc., even those that are hard to quantify, can also be quantified. Artificial Neural Network is used for classifying the coal dataset. The project is designed using Python as front end environment. The coding language used is the Python3.7

Keywords—Coal Classification, Centroid Contour, Deep Learning, Object Recognition.

I. INTRODUCTION

Nowadays, coal is the most required energy source for new society. It has a complex recovery processes, and can be mixed with considerable amount of Silicon Dioxide Sio2 as which is called as coal gangue.

The coal gangue's main components are both a) Al2o3 and b) Sio2, which are sulfur rich and great quantities of the heavy metals like arsenic, cadmium, chromium, copper, etc. Burning these coal gangue will result in emission of hazardous substances which create environmental pollution.

Moreover, when comparing with the coal, combustion value of the coal gangue is lower, which minimize the total energy for coal mixed with coal gangues. So, sorting the coal gangue from its main coal is an extremely important process and it also has two traditional sorting formula / methods: i) human sorting and ii) wet cleaning methods.

A sieving machine sorts pure / raw coal into coal equal to or > 100 mm and also &<100 mm; a new transportation system is used for transporting the coal from underground to basement ground; and coal equals or >=100 mm is transported to sort workshop in which skilled workers sort coal gangue from its coal based on gray values with texture differences. In addition to these traditional methods, representative research methods also cover ray casting, radar detection, mechanical vibration, color separation, etc., which are having good detection methods and properties, but they also have high requirements also for runtime environments and can impact human health.

With the computer technology development, Image Net is combined with convolutional neural networks (CNNs), as well as deep learning developed rapidly. When Compared with old traditional sorting methods, latest object detection algorithms could learn from sample images using CNN, that extract features of coal with coal gangue and are having most significant advantages, like high identification speed with high precision.

Distinguishing coal from coal gangue is an important working part of coal industry and is mainly conducted by using human sorting at present.

Consequently, most considerable man power is required, which adds the risk burden for companies and so results in poor efficiency. As a main important branch of artificial intelligence, deep learning has been widely applying in numerous fields, main in machine vision/voice recognition, and its performance is enhanced greatly when compared with performances of traditional learning methods, and it is having good a transfer learning ability also.

This study proposed an improved Artificial Neural Network algorithm as the classic deep learning method for intelligent and highly accurate recognition of coal gangue. Compared to the YOLO algorithms, this ANN has better anchor value by using cluster analysis application for different data sets, and a good anti- interference ability for minimizing impacts from mine dust/shock and which acquires the more richer detailed information by adding number of layers of feature pyramid

a) Auto-inspecting and grading system for machine vision to extract and analyze color, size, shape, and surface texture. The proposed extraction margin method could be carried out roughly and there is still a variation between both the margin of extracted shapes, polygons, and shape margins of the original image. Therefore, to improve the method for capturing the coal outline, this project proposes a NN to classify coal features. As a result, the captured image is consistent with original coal images. Since image recognition technology for quantifying three dimensional features, are difficult, and accuracy of quantified value could not be verified, accuracy of feature search query is definitely impacted and so they cannot be performed. Therefore, this project applied NN to those coal features to accurately quantify them.

The rest of this paper is organized as follows: Section 2 reviews the existing security approaches under recent studies and explains previous works and their drawbacks. Section 3 provides proposed methodology of the study. Section 4 provides finds and Section 5 is conclusion of the study.

II. LITERATUREREVIEW

In this paper [1] the authors stated that to solve problems of the difficult poor feature credibility, feature extraction, and low recognition accuracy of coal and gangue, so this paper utilizes a difference in coal's dielectric properties, gangue and combining with a SVM (support vector machine) to propose a recognition method based on dielectric characteristics of coal gangue. The influence rule of edge effect of electrode plate in capacitance values were analyzed when the thickness of electrode plate changes. By changing frequency and voltage of excitation source, dielectric constant curves of coal and gangue in it versus frequency / voltage are obtained.

Combined with the Kalman filter, adaptive noise complete-set empirical mode decomposition (CEEMDAN) denoising method was improved, which results in signal with higher signal-to-noise ratio/lower root mean square error after denoising. An effective value/frequency of the denoised response signal were extracted to construct feature vector sets to form the training set / test set. Data of training set is given as input to SVM for training intelligent classification model, test set is used to test the SVM classification effect, and make the classification accuracy > 99%.

Unlike those of the probabilistic neural networks (PNN), intelligent classification model as well as learning vector quantization (LVQ) NN (neural network) classification model, recognition / classification accuracies of three reach 99%, but the classification speed of SVM is the most fastest, by taking 0.007915s, which fully reflecting feasibility as well the efficiency of capacitance method in identifying coal with the gangue. Here in this paper, SVM was applied to identify coal and gangue, accurate and efficient identification results are obtained, which provided the new feasible solution in research in coal gangue identification.

Normally, coal gangues produced will be in the large amount during coal mining. Coal gangue is a type of the solid waste with the low carbon content, accounts for 10%-14% of the raw coal. The main components are organic molecules and hydrocarbon, active while main components of coal gangue; Al_2O_3 / SiO_2. The coal gangue is mixed with the coal; it will not only minimize the quality of coal combustion, but also increase emission of waste gases. To improve quality of coal combustion and reduction of emission of poisonous harmful gases, separation of the coal gangue from raw coal is an important problem in coal mine/ engineering.

Coal gangue recognition is one of the key technologies in gangue separation. Hou et al. [6 - 8] analyzed the difference data between coal with gangue in terms of i) surface texture and ii) grayscale characteristics, and then combined them with classification algorithm to recognize the coal gangue.

Because of the coal’s texture and grayscale characteristics along with its gangue are greatly affected by the light, recognition accuracy might not high.

Liu et al. [9 - 13] found that morphological differences between the coal / coal gangue is on the basis of studying i) texture and ii) gray features, and introduced multifractal for extracting geometric features of coal gangue , however multifractals geometric features‘ extraction process is more complex and has poor adaptability.

Alfarzaeai et al. [14-18] studied a near infrared spectrum, thermal infrared spectrum and found coal and its gangue’s multispectral characteristics, and got high recognition accuracy in laboratory environment using one of the neural network algorithms. Still, this technology was not mature, and it was difficult to apply in practical because of influence of the ambient temperature as well as light. Zhao et al. studied the radiation and attenuation characteristics of X-rays , γ -rays in the coal and coal gangue.

Coal gangues are identified in essence through their attenuation characteristics of two: X-rays and γ- rays; but , radiation produced by the rays will cause physical harm to the workers, and equipment’s maintenance cost will also be high. Wang et al. discussed a method of measuring volume using 3D laser scanning technology, which is combined with dynamic weighing technology for identifying coal gangue. The volume is an estimated value; the measurement error is large relatively.

Yang et al. studied the vibration signals of coal and coal gangue particles colliding with metal plates, and extracted the eigenvalues of the signals in combination with machine learning algorithms for identifying coal gangue, damage identification, reduces the quality of coal. Finding the recognition feature with high reliability, easy extraction and then few side effects has become a difficult task in the current recognition of coal and coal gangue. Nelson et al. studied the dielectric properties of pulverized coal, and found that the dielectric constant of pulverized coal decreases regularly with increasing frequency, which provides a reference for studying dielectric properties of coal with coal gangue.

Muhammad et al. as a team conducted research in cutting-edge and pioneering studies in the signal desiccating, signal decomposition and the machine learning, with good references. In this paper, a difference between dielectric properties of coal gangue are studied, and a recognition method of coal and its gangue based on the dielectric properties was proposed. This method realizes nondestructive testing in coal and coal gangue.

X- ray and γ-ray identification equipments, have high radiation intensity; so the internal features of coal and gangue that cannot be perceived just by image recognition could be obtained. Here in this study, coal and gangue collection were obtained from Huainan mining area, and SVM intelligent classification models were trained by combining coal and gangue’s dielectric constant characteristics with the SVM.

Test results showed that capacitance method had high accuracy and strong timeliness in finding coal and gangue, and had great research prospects. They also concluded that according to differences in the dielectric properties coal and its gangue, dielectric constants of coal and gangue are proposed first as the identification characteristics, which provided a new method for identification of coal and gangue.

Also in this paper, a new capacitance identification method using coal and gangue with regular shapes were conceived, and remarkable recognition, classification results were obtained by combining SVM intelligent classification models. The main contributions of that paper were as follows: 1) The capacitance identification model of coal and gangue was established, and finite element simulation analysis of capacitor model was carried out.

Influence of the edge effect produced by plate thickness on the calculation of capacitance value was obtained, the calculation formula of the capacitance value was modified for accurately calculating the capacitance value of the capacitor when medium changes.

In this paper [2] the authors stated that bounding box regression is a crucial step in detecting object. In existing methods, while `n-norm loss were adopted widely for bounding box regression, it was not tailored to valuation metric, i.e., Intersection over Union (IoU).

Recently, IoU loss and generalized IoU (GIoU) loss have been introduced to benefit IoU metric, however, still suffer from a problem of i) slow convergence and ii) inaccurate regression. The authors proposed in this paper, a Distance- IoU (DIoU) loss by taking the normalized distance between the predicted box and target box, which converges faster in training than a) IoU and b) GIoU losses.

Furthermore, this paper summarized three geometric factors in the bounding box regression,i.e., a) overlap area, b) central point distance and c) aspect ratio, based on which the Complete IoU (CIoU) loss was proposed, thereby leading for faster convergence and better performance. Using DIoU and CIoU losses into the state- of-the-art object detection algorithms, e.g., SSD, YOLO v3 and Faster RCNN, they achieved notable performance gains not only in IoU metric but also GIoU metric. In addition, DIoU could be easily adopted into non-maximum suppression (NMS) for acting as a criterion for further boosting performance improvement.

Object detection is one of the key issues in machine vision tasks, and has received considerable research attention for recent decades (Redmonetal.2016; Redmonand Farhadi 2018; Wang et al. 2019; 2018, Ren et al. 2015; Yang et al. 2018; He et al. 2017). Generally, existing object detection methods are categorized as: one- stage detection, like YOLO series (Redmonetal.2016) and SSD (Liu et al. 2016), a two-stage detection, such as R- C N N s e r i e s (G i r s h i c k e t a l . 2 0 1 4 ; Renetal.2015;Heetal.2017), and also even multistage detection, like Cascade R-CNN (Caiand Vasconcelos 2018). Despite of these different detection frameworks, bounding box regression is the most crucial step for predicting a rectangular box to locate the target object.

They concluded that in that paper, that they proposed two losses, i.e., i) DIoU loss and ii) CIoU loss, for bounding box regression with DIoUNMS to suppress redundant detection boxes. Using direct minimization of the normalized distance of two central points, DIoU loss achieved faster convergence than GIoU loss CIoU loss take three geometric properties into account, i.e., i) overlap area, ii) central point distance and iii) aspect ratio, and leads to faster convergence and better performance. The proposed losses and DIoU-NMS could be easily incorporated to any of the object detection pipelines, and could achieve superior results on benchmarks.

In this paper [3] the authors stated that lately, maximum modern-day item detection structures undertake anchor field mechanism to simplify the detection model. Neural networks most effective need toregress the mapping members of the family from anchor containers to ground fact containers, then prediction containers can be calculated the usage of records from outputs of networks and default anchor bins.

But, whilst the hassle turns into complicated, the quantity of default anchor boxes will increase with big risk of over-becoming during education. On this paper, they adopted an adaptive anchor box mechanism that one anchor box can cover more ground reality containers.

So networks only need a few adoptive anchor bins to

resolve the same hassle and the version may be more

robust. The sizes of adaptive anchor bins might be adjusted mechanically in line with the depth accrued via a Time of Flight (TOF) digital camera.

The network adjusts the aspect ratios of anchor boxes to get final prediction boxes. The experimental consequences exhibit that the proposed method can get more correct detection consequences. Specially, the use of the proposed adaptive anchor field mechanism, the mean common Precision (mAP) of YOLO-v2 and YOLO-v3 networks increases glaringly on open public datasets and their self-built battery photograph dataset.

Furthermore, the visible outcomes of prediction comparisons also illustrate that the proposed adaptive anchor container mechanism can obtain better performance than unique anchor box mechanism.

In this paper [4] the authors stated that organizing information into practical groupings is one of the maximum essential modes of knowledge and getting to know. As an instance, a not unusual scheme of clinical classification places organisms into a system of ranked taxa: area, nation, phylum, class, and many others.

Cluster evaluation is the formal study of strategies and algorithms for grouping, or clustering, gadgets in keeping with measured or perceived intrinsic traits or similarity.

Cluster evaluation does no longer use class labels that tag items with earlier identifiers, i.e., magnificence labels.

The absence of class statistics distinguishes records clustering (unsupervised gaining knowledge of) from classification or discriminant evaluation (supervised mastering). The intention of clustering is to find structure in information and is therefore exploratory in nature. Clustering has a protracted and wealthy history in a selection of clinical fields.

One of the maximum famous and simple clustering algorithms, k-method, was first posted in 1955. In spite of the reality that k-method become proposed over 50 years ago and lots of clustering algorithms were posted due to the fact that then, ok-manner remains extensively used. This speaks to the issue of designing a general purpose clustering set of rules and the ill-posed problem of clustering.

The author supplied a brief evaluation of clustering, summarize widely known clustering techniques, talk the important demanding situations and key problems in designing clustering algorithms, and point out some of the emerging and useful studies guidelines, which include semi-supervised clustering, ensemble clustering, simultaneous characteristic choice throughout records clustering and big scale data clustering. Advances in sensing and storage generation and dramatic increase in packages inclusive of net seek, digital imaging, and video surveillance have created many excessive-extent, high- dimensional information units. Its miles estimated that the virtual universe fed on approximately 281 Exabyte's in 2007, and it miles projected to be 10 times that size by way of 2011. (One Exabyte is ~1018 bytes or a million terabytes) [Gantz, 2008]. Maximum of the records is stored digitally in electronic media, accordingly providing massive potential for the improvement of automatic records analysis, category, and retrieval techniques. Further to the growth in the quantity of statistics, the type of available information (text, image, and video) has additionally extended. Inexpensive digital and video cameras have made to be had big documents of images and motion pictures. The prevalence of RFID tags or transponders because of their low fee and small length has resulted in the deployment of tens of millions of sensors that transmit statistics regularly. E-mails, blogs, transaction facts, and billions of net pages create terabytes of new records every day. A lot of those facts streams are unstructured, adding to the difficulty in analyzing them. The growth in each the extent and the kind of statistics requires advances in method to robotically recognize, system, and summarize the facts.

Information evaluation techniques are extensively categorized into important types [Tukey, 1977]: (a) exploratory and/or descriptive, that means that investigator may now not have pre-specified fashions and/or hypotheses but wants to understand overall characteristics or shape of high dimensional information, and (b) confirmatory or inferential, which means that the investigator desires to verify the validity of a hypothesis/version or a fixed of assumptions given the available information.

More statistical techniques are proposed now to analyze data, like variance analysis, discriminant analysis, linear regression, principal component analysis, multidimensional scaling, canonical correlation analysis, factor analysis, and cluster analysis to name a few.

A useful overview of the sear given in [Tabachnick Fidell, 2007].

In pattern recognition methods, data analysis is dealt with predictive modeling: by giving some training data, an author wants to predict behavior of the unseen test data. This task is referred to as learning. Often, the clear distinction is made among learning problems that are (a) supervised (classification) or (b) unsupervised (clustering), first involving labeled data only (training patterns with well known category labels) but latter involving only unlabeled data [Duda et al. 2001]. Clustering is the more difficult and challenging problem compaed to classification. There is a growing interest in a hybrid setting, called semi supervised learning [Chapelle et al., 2006]; in semi-supervised classification, labels of only a small portion of the training data set are available.

The unlabeled data, instead of being eliminated, are used in learning process. In semi-supervised clustering, instead of specifying class labels, the pair- wise constraints are specified, which is one of the weaker ways of encoding the prior knowledge.

Pair-wise must-link constraint points to the requirement that those two objects should be assigned same cluster label, whereas cluster labels of two objects participating in a cannot-link constraint must be different.

Constraints are particularly beneficial in data clustering [Basu et al., 2008, Lange et al., 2005], but precise definitions of underlying clusters were not found.

In the searching of good models, anybody would like to add the entire available information, no matter it is unlabeled data, data with constraints, and/or labeled data.

Figure 1 illustrates a spectrum of different types in Learning problems of interest in machine learning and pattern

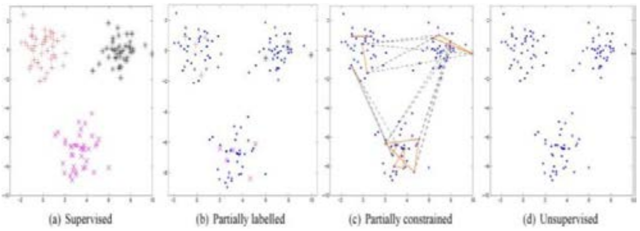

Figure 2.1: Learning problems: dots correspond to points without any labels. Points with labels are denoted by plus signs, asterisks, and crosses. In (c), the must-link and cannot-link constraints are denoted by solid and dashed lines, respectively (figure taken from [Lange et al., 2005]). Cluster analysis is one of the main goals of data clustering, and is to find natural grouping(s) of group or set of points, patterns, and/or objects. Webster [Merriam- Webster Online Dictionary, 2008] defines cluster analysis as "a classification technique of statistical to discover whether the individuals of the population fall into various groups by making quantitative comparisons in multiple characteristics."

A clustering example is shown in Figure 2. The main objective is developing an automatic algorithm that discovers the natural groupings (Figure 2 (b)) in unlabeled data (Figure 2 (a)). Another definition of clustering can be stated as follows:

Given a representation of 'n' objects, find 'K' groups based on the measure of similarity such that similarities between objects in same group are high while similarities between objects in the different groups are low. But, what is a notion of similarity? What is definition of the cluster? Figure 2 explains that clusters are differ in terms of their size, shape, and density.

The presence of noise in the data makes the detection of the clusters even more difficult. An ideal cluster can be defined as a set of points that is compact and isolated. In reality, a cluster is a subjective entity that is in the eye of the beholder and whose significance and interpretation requires domain knowledge. But, while humans are excellent cluster seekers in two and possibly three dimensions, we need automatic algorithms for high dimensional data. It is a challenge along with unknown number of clusters for given data that has resulted in the thousands of clustering algorithms which have been published and that continue to appear.

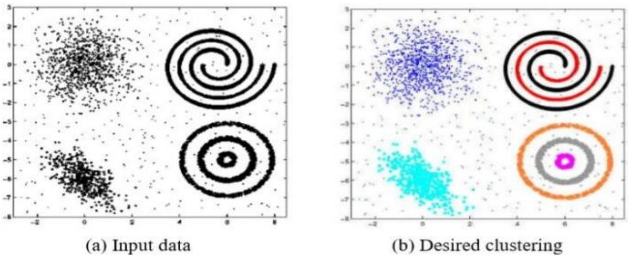

Figure 2: Diversity of clusters. The seven clusters in (a) (denoted by seven different colors in 1(b)) differ in shape, size, and density. Although these clusters are apparent to a data analyst, none of the available clustering algorithms can detect all these clusters.

Clustering algorithms are broadly divided into two groups: a) hierarchical and b) partitional. Hierarchical clustering algorithms find nested clusters recursively either in agglomerative mode starting with each data point in its own cluster and then merging most similar pair of clusters successively to form a cluster hierarchy; otherwise in divisive (top down) mode starting with all the data points in one cluster and then recursively dividing each cluster into smaller clusters.

Comparing with hierarchical clustering algorithms, the partitional clustering algorithm finds all the clusters simultaneously as the partition of the data and don

't impose the hierarchical structure. Input to a hierarchical algorithm is an n*n similarity matrix, where 'n is the number of objects taken for clustering clustered. But on the other hand, the partitional algorithm could be used either an nxd pattern matrix, where ‘n objects are embedded in the dimensional feature space, or an nxn similarity matrix.

Note that the similarity matrix is easily derived from the pattern matrix, however ordination methods such as MDS (multidimensional scaling) are needed to derive a pattern matrix from a similarity matrix.

The well-known hierarchical algorithms are single- link and complete-link; K-means is the most popular and simplest partitional algorithm. Since partitional algorithms prefer in pattern recognition due to the nature of available data, they coveraged here is focused on these algorithms. Thousands of clustering algorithms are being proposed in literature in various scientific disciplines. This makes it difficult to review the entire published approaches. Still, many clustering methods differ on the choice of objective function, probabilistic generative models, and heuristics. The authors briefly reviewed some of the important major approaches.

Clusters are defined as high density regions in feature space separated by low density regions.

Algorithms following this clusters directly search for connected dense regions in feature space. Different algorithms use various definitions of connectedness.

Jarvis-Patrick algorithm defines similarity between the pair of points as a number of common neighbors they share, where neighbors are points present in the region of a pre-specified radius around the point [Frank and Todeschini, 1994]. Ester et al. [Ester et al. 1996] proposed a DBSCAN clustering algorithm, which is similar to Jarvis-Patrick algorithm. It directly tracks for connected dense regions in feature space by estimating density using the Parzen window method. The Jarvis-Patrick algorithm and DBSCAN performances depend on two parameters: a) neighborhood size in terms of distance, and b) the minimum number of points in a neighborhood for its inclusion in a cluster. Moreover, a number of probabilistic models are being developed for data clustering which models the density function by the probabilistic mixture model.

These approaches are being assumed that data are generated from the mixture distribution, in which each cluster is described by more mixture components [McLachlan and Basford, 1987]. The EM algorithm [Dempster et al. 1977] is used to infer parameters in the mixture models.

III. PROPOSEDMETHODOLOGY

In existing system, the image is being visualized manually and gangue presence is checked by professional. Normally images are processed with median filter so that the noise pixels are eliminated and image clarity is improved. Only through manual checking, gangue content presence could be identified.

Some studies classified the tumor types using augmented gangue region of interest, image dilatation, and ring-form partition. They extracted features using intensity histogram, gray level co-occurrence matrix, and bag-of-words models, and achieved some accuracy.

- Median filter process required.
- Not effective when gangue data is very low in size.
- Accurate image processing for gangue presence is not possible.
- Manual verification/checking are required.

In proposed system, the gray scale image is taken.

The RGB image if taken, is converted into gray scale image first. Then all the images are resized into same size. Then the training data set image with tumor class factor ‘yes’ are taken along with ‘no’. For each image, all the pixels’ grayscale value are found out and written in a row.

So the total number of rows is equal to total number of images. The number of columns is the number of pixels in the image. These data is saved in comma separated file. For testing data, all these operations are carried out and saved in another comma separated value file. Then Convolutional neural network is applied to train the model with test data.

The accuracy is found out and displayed. From the given test image, it can be found out as gangue present or not by checking with training data images.

- Median filter process is not required.
- Effective even when tumor data is very low in size.
- Accurate image processing for tumor presence is possible.
- Manual verification/checking are not required.

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- CNN is the best algorithm so that accuracy will be more.

IV. FINDINGS

- The proposed scheme will be helpful in the diagnosis of coal gangue.
- The proposed method was successfully applied in the coal image with very high precision.
- Extracting gangue features of the coal is implemented.
- The proposed system detects and classifies the examined gangue with high accuracy.

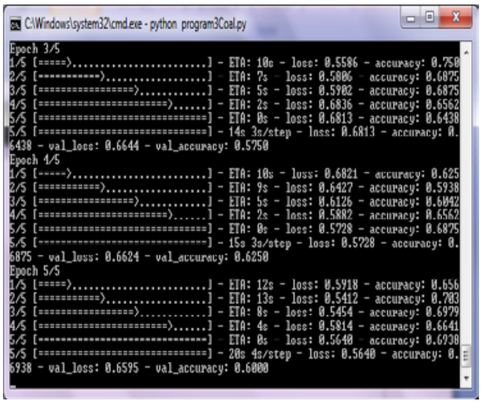

Figure4.2 Neural Network Iterations

REFERENCES

[1] Guo Y, WangX, Wang S, Hu K, Wang W. (2021). “Identification method of coal and coal ganguebased on dielectriccharacteristics,”IEEE Access.,vol. 9, pp. 9845- 9854,Jan. 202

[2] ZhaohuiZheng,Ping Wang,Wei Liu, Jinze Li, RongguangYe,DongweiRen. “Distance-IoULoss: Fasterand BetterLearning for Bounding Box Regression,” Presentedat AAAIConference on Artificial Intelligence 2020.[Online].Available:https://ojs.aaai.org//index.php/AAAI/article/view/6999.

[3] Gao, Mingyu, et al. “Adaptive anchor box mechanism to improve the accuracy in the object detection system,” Multimedia Tools and Applications.,vol. 78, no. 19, pp. 27383-27402, Oct. 2019.

[4] Jain, Anil K. . “Data clustering:50 years beyondK- means.” PatternRecognitionLetters., vol. 31, no. 8, pp. 651- 666,June. 2010.

[5] S. Ren, K. He, R. Girshickand J. Sun, “Faster R- CNN:Towards Real-Time Object Detection with Region Proposal Networks,” IEEE Transactions on Pattern Analysis and Machine Intelligence.,vol. 39,no. 6, pp. 1137-1149,June. 2017.

[6] Hou Wei. Identification of Coal and Gangue by Feed- forward Neural Network Based on Data Analysis
[J]. International Journal of Coal Preparation and Utilization., vol. 39, no. 1, pp. 33-43, Jan. 2019.

[7] Dou, Dongyang; Zhou, Deyang; Yang, Jianguo, et al. Coal and gangue recognition under four operating conditions by using image analysis and Relief-SVM [J]. International Journal of Coal Preparation and Utilization., vol. 40, no. 7, pp.473-482, Jul. 2020.

[8] Li, , Man; Duan, Yong; He, Xianli, et al. Image positioning and identification method and system for coal and gangue sorting robot [J]. International Journal of Coal P r e p a r a t i o n a n d U t i l i z a t i o n . , M a y.2020DOI.10.1080/19392699.2020.1760855.

[9] Jian Song. “Research on Identification Algorithm of Coal and Gangue Based on Image Feature,” M.S. thesis, Dept. Computer science and technology., Hebei University of Engineering., Hebei, China, 2016.

[10] Xianmin Ma, Xiaoru ng. “Coal Gangues Automation Selection System Based on ARM Core and CAN Bus,” Chinese Journal of Scientific Instrument.,vol. 26, no. 8, pp. 305-307, 318,August 2005.

[11] Hailing Zhang, Jialin Wang, , Jiansheng Wu, Rong Shi. “Application of Rough Sets Theory to Image Enhancement Processing,” Journal of Tongji University (Natural Science)., vol. 36, no. 2, pp. 254-257, Feb. 2008.

[12] Wanzhi Wang, Zengcai Wang. “Characteristic Analysis and Recognition of Coal and Rock Based on Visual Technology,” Coal Technology., vol. 33, no. 10,

pp. 272-274, Oct 2014.
[13] Yunxia Wu, Yimin Tian. “Methodof coal-rock image feature extraction and recognition based on dictionary learning,” Journal of China Coal Society., vol. 41, no. 12, pp. 3190-3196, Dec 2016.
[14]] J. Redmon, S. Divvala,R. Girshickand A. Farhadi, “You only look once: Unified real-time object detection,” in Proc. CVPR, Las Vegas, NV, United States, 2016, pp. 779-788.
[15] Ping Hu, Hanlin Zeng, KeyanHuo. “Research on density identification system of coal and refuse based on image processing technology,” Goal Preparation Technology., no. 2, pp. 69-73, Apr.2015.
[16] Guo Y, Wang, X, Wang S, Hu K, Wang W. (2021). “Identification method of coal and coal gangue based on dielectric characteristics,” IEEE Access., vol. 9, pp. 9845- 9854 Jan 2021’
[17] Xijie Dou, Shibo Wang, Yang Xie, Tong Xuan. “Coal and gangue identification based on IMF energy moment and SVM, ” Journal of Vibration and Shock, vol. 39, no. 24, pp. 39-45, Dec 2020.
[18] Wei Hou. “Identification of Coal and Gangue by Feed- forward Neural Network Based on Data Analysis,” International Journal of Coal Preparation and Utilization, vol. 39, no. 1, pp.33-43, Jan 2019.