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Multiple Coal Classification using Deep Learning Techniques

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Abstract: *Coal is mainly energy in the word which play a very important role in the development of the national economy. But there are plenty of coal gangue in addition to coal in the process of mining. The traditional sorting is mainly used by manual selection and mechanical separation. This project explores a new coal classification model based on features extraction and deep learning. In view of the characteristics of high dimensionality, strong correlation, and high redundancy of spectral data, this project proposes to combine features extraction with Convolutional neural network to solve the problem of coal classification, and to further improve the classification accuracy. An improved classification algorithm is proposed, and the improved deep learning algorithm is used to improve and optimize the structure and training parameters of the model. Finally, analyse the results in terms of execution time and accuracy parameter.*

Keywords: Artificial Intelligence (AI), Convolutional Neural Network (CNN), Edge Histogram Descriptor (EHD), Deep Learning (DL), Machine Learning (ML), Support Vector Machine (SVM), etc.

I. INTRODUCTION

Coal is primarily used as fuel to generate electric power in the India. In coal-fired power plants, bituminous coal, subbituminous coal, or lignite is burned. The heat produced by the combustion of the coal is used to convert water into high-pressure steam, which drives a turbine, which produces electricity. There are four major types (or “ranks”) of coal. Rank refers to steps in a slow, natural process called “coalification,” during which buried plant matter changes into an ever denser, drier, more carbon-rich, and harder material.

The four ranks are:

Anthracite: The highest rank of coal. It is a hard, brittle, and black lustrous coal, often referred to as hard coal, containing a high percentage of fixed carbon and a low percentage of volatile matter.

Bituminous: Bituminous coal is a middle rank coal between subbituminous and anthracite. Bituminous coal usually has a high heating (Btu) value and is used in electricity generation and steel making in the United States. Bituminous coal is blocky and appears shiny and smooth when you first see it, but look closer and you might see it has thin, alternating, shiny and dull layers.

Lignite: Lignite coal, aka brown coal, is the lowest grade coal with the least concentration of carbon. Lignite has a low heating value and a high moisture content and is mainly used in electricity generation.

Peat: The precursor to coal is peat. Peat is a soft, organic material consisting of partly decayed plant and mineral matter. When peat is placed under high pressure and heat, it undergoes physical and chemical changes (coalification) to become coal. Existing system present novel methods for automatic mineral identification based on combining data from different spectroscopic methods. Then implemented an artificial neural network which is used for the classification of coals.

Optical data using thin sections is acquired using the rotating polarizing microscope stage, which extracts a basic set of seven primary images during each sampling. A selected set of parameters based on hue, saturation, intensity and texture measurements are extracted from the segmented minerals within each data set. Texture parameters are shown to have the ability to classify colorless minerals. The neural network is trained on manually classified mineral samples.

Finally Concatenated convolutional neural network (Con-CNN) method is used for classifying the geologic rock type based on petrographic thin sections. This project presents a novel method for identifying coal and rock based on features extraction and deep convolutional neural network (CNN). The features extraction is done with help of Active contour method. And regularization methods are introduced in this project to solve the over fitting problem of CNN and speed up the convergence: dropout, weight regularization, and batch normalization. Then the coal-rock image information is enriched by means of data augmentation, which significantly improves the performance. The shearer cutting coal-rock experiment system is designed to collect more real coal-rock images, and some experiments are provided. The experiment results indicate that the network we designed has better performance in identifying the coal-rock images.

II. LITERATURE REVIEW

Recognizing coal and coal gangue is a crucial element of the coal industry, and it is currently done primarily through human sorting. As a result, a large amount of labour is required, putting a strain on businesses and resulting in low efficiency. Deep learning, as a branch of artificial intelligence, has been widely used in many fields, particularly machine vision and voice recognition. Its performance is significantly better than standard learning methods, and it also has a good transfer learning capacity.

Coal is one of the most important energy sources in modern society. Its recovery process is complex, and coal is mixed with a considerable amount of coal gangue.

The major components of coal gangue are Al2o3 and Sio2, which are sulphur-rich and include large amounts of heavy metals such arsenic, cadmium, chromium, copper, tribute, and other heavy metals. When coal gangue is burned, harmful compounds are released into the atmosphere, causing pollution. Furthermore, coal gangue has a lower combustion value than coal, which can diminish the overall energy for coal combined with coal gangue. Sorting coal gangue from coal is a critical connection, and there are two classic techniques for doing so: manual sorting and wet cleaning. A sieving machine sorts raw coal into coal with a diameter of 100 mm or greater and coal with a diameter of less than 100 mm; a transportation system transports coal from underground to ground; and coal with a diameter of 100 mm or greater is transported to a sorting workshop, where skilled workers sort coal gangue from coal based on grey values and texture differences. Ray casting, radar detection, mechanical vibration, colour separation, and other representative research approaches, in addition to the foregoing classic methods, have good detection properties but have high requirements for runtime conditions and can influence human health.

ImageNet has been coupled with convolutional neural networks (CNNs) as computer technology has progressed, and deep learning has exploded [6]. Object detection algorithms may learn from sample photos using a CNN, which can extract features of coal and coal gangue and has substantial advantages, such as high identification speed and precision, as compared to standard sorting approaches. In the loss function for the object identification job, the classification loss and bounding box regression loss are widely utilised.

Many external elements, such as lighting conditions, physical shock, coal dust dispersion, and so on, might have an impact on image photography and transmission.

As a result, bias in images is unavoidable since real photos of coal gangue have distorted spectral features, spatial placements, and so on, introducing significant noise in the coal and coal gangue images. These noises can wreak havoc on picture extraction, effective image information, and subsequent image processing, hence image pretreatment is used to improve image creation quality and overcome the aforesaid disadvantage. The results of various algorithms that process a large number of photos are compared in this research.

III. METHODOLOGY

Image Acquisition:

Coal is primarily used as fuel to generate electric power in the India. In coal-fired power plants, bituminous coal, subbituminous coal, or lignite is burned. In this module, we can upload the datasets related to coal from KAGGLE website. And stored the images in any type and any size.

Coal Types:

Different coal types are all minerals and rocks made largely of carbon. This fossil fuel generates ~40% of the world's electricity and about 25% of the world's primary energy. However, not all coal used is the same; it comes in different quantity levels of carbon—which dictates the quality of the coal. Higher quality coal produces less smoke, burns longer, and provides more energy than lower quality coal. The table below includes the carbon contents, and energy densities of coal. In addition, it states the moisture content before drying, and the amount of volatile content, after it's dried.

Coal Description:

Coal	Dry, Carbon Content (%)	Moisture content before drying (%)	Dry, Volatile Content (%)	Heat Content (MJ/kg)
Anthracite	86-92	7-10	3-14	32-33
Bituminous Coal	76-86	8-18	14-46	23-33
Lignite	65-70	35-55	53-63	17-18
Peat	<60	75	63-69	15

Pre-processing:

Here, Coal image can input to the system. The user has to select the required object frame image for further processing. Then each image is resized to 256*256. Then implement median filter to remove noises from images. The median filter is a nonlinear digital filtering technique, often used to remove noise from an image or signal. Such noise reduction is a typical pre-processing step to improve the results of later processing (for example, edge detection on an image). Median filtering is very widely used in digital image processing because, under certain conditions, it preserves edges while removing noise (but see discussion below), also having applications in signal processing.

The main idea of the median filter is to run through the signal entry by entry, replacing each entry with the median of neighbouring entries. Median filtering is a nonlinear method used to remove noise from images. It is widely used as it is very effective at removing noise while preserving edges. It is particularly effective at removing 'salt and pepper' type noise. The median filter works by moving through the image pixel by pixel, replacing each value with the median value of neighboring pixels. The pattern of neighbors is called the "window", which slides, pixel by pixel over the entire image pixel, over the entire image. The median is calculated by first sorting all the pixel values from the window into numerical order, and then replacing the pixel being considered with the middle (median) pixel value.

Features Extraction:

Feature learning comprises a set of algorithms to transform labelled or unlabelled data to a new space, where it can capture the parameters and patterns of variation by disentangling the hidden features. Features are learned through supervised and unsupervised learning scheme. Numerous unlabelled data is available in each domain, e.g., images, text data, speech, which contain several patterns of variation that can easily be collected for feature extraction, e.g., from pre-processed image.

The task of feature extraction from unlabelled data is known as unsupervised feature learning. Data-adaptive representations are dependent on the statistics of data. Such representations are learned directly from the observed data by optimizing some measure that quantifies the desired properties of the representation. In linear sparse coding, the goal is to find a decomposition in which the hidden components are sparse, meaning that they have probability densities which are highly peaked at zero and have heavy tails. This basically means that any given input vector can be well represented using only a few significantly non-zero hidden coefficients.

Coal Classification:

The classification is the final step of the system. After analyzing the structure, each section individually evaluated for the probability of true positives. Multiple coals are classified using Convolutional neural network algorithm. CNNs represent feed-forward neural networks which encompass diverse combos of the convolutional layers, max pooling layers, and completely related layers and Take advantage of spatially neighbourhood correlation by way of way of imposing a nearby connectivity pattern among neurons of adjacent layers. Convolutional layers alternate with max pooling layers mimicking the individual of complex and clean cells in mammalian seen cortex.

A CNN includes one or extra pairs of convolution and max pooling layers and ultimately ends with completely related neural networks. The hierarchical structure of CNNs is steadily proved to be the most efficient and successful manner to analyze visible representations. The fundamental challenge in such visual tasks is to model the intra-class appearance and

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shape variation of objects. The coal data with hundreds of spectral channels can be illustrated as 2D curves. We can see that the curve of every class has its own visual shape which is different from other classes, although it is relatively difficult to distinguish some classes with human eye (e.g., gravel and self-blocking bricks).

We know that CNNs can accomplish competitive and even better performance than human being in some visual problems, and its capability inspires us to study the possibility of applying CNNs for classify the coal features. The CNN varies in how the convolutional and max pooling layers are realized and how the nets are trained. This network varies affording to the spectral channel size and the number of output classes of input coal data. So, our proposed work overcomes irregular boundaries separation in coal image classification with features extraction.

Edge Histogram Descriptor (EHD):

Edge Histogram Descriptor is the histogram generated using the edge pixels. The edge distribution is a good texture signature and also useful for image-to-image matching. This approach is not rotation invariant. The MPEG-7 standard defines the edge histogram descriptor (EHD) in its texture part. The distribution of edges is useful for image-to-image matching. But this descriptor is not effective for the rotation invariance.

SUPPORT VECTOR MACHINE:

Support Vector Machine or SVM is one of the most popular Supervised Learning algorithms, which is used for Classification as well as Regression problems. However, primarily, it is used for Classification problems in Machine Learning. The goal of the SVM algorithm is to create the best line or decision boundary that can segregate n-dimensional space into classes so that we can easily put the new data point in the correct category in the future. This best decision boundary is called a hyperplane.

GREY SCLAED IMAGE

IV. ALOGRITHM

Convolutional neural network algorithm-A **Convolutional Neural Network (ConvNet/CNN)** is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other. The pre-processing required in a ConvNet is much lower as compared to other classification algorithms. While in primitive methods filters are hand-engineered, with enough training, ConvNets have the ability to learn these filters/characteristics. Through the application of suitable filters, a ConvNet may successfully capture the Spatial and Temporal dependencies in a picture. Due to the reduced number of parameters involved and the reusability of weights, the architecture performs superior fitting to the picture dataset.

In other words, the network may be trained to better understand the image's sophistication. The Convolution Operation's goal is to extract high-level characteristics from the input image, such as edges. There is no need to limit ConvNets to just one Convolutional Layer. The first ConvLayer is traditionally responsible for capturing Low-Level information such as edges, colour, gradient direction, and so on. With the addition of layers, the architecture adjusts to the High-Level characteristics as well, giving us a network that understands the photos in the dataset in the same way that we do. The

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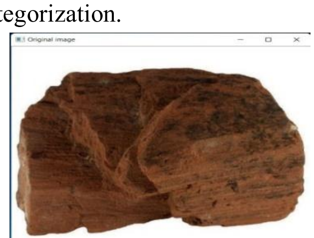
operation produces two types of results: one in which the dimensionality of the convolved feature is lowered when compared to the input, and the other in which the dimensionality is either increased or unchanged. This is accomplished by using Valid Padding in the first case and Same Padding in the second. On the other hand, if we perform the same operation without padding, we are presented with a matrix which has dimensions of the Kernel (3x3x1) itself

Valid Padding: The Pooling layer, like the Convolutional Layer, is responsible for shrinking the Convolved Feature's spatial size. Through dimensionality reduction, the computer power required to process the data is reduced. It's also beneficial for extracting rotational and positional invariant dominant features, which helps keep the model's training process running smoothly. Pooling can be divided into two types: maximum pooling and average pooling. The maximum value from the portion of the image covered by the Kernel is returned by Max Pooling. Average Pooling, on the other hand, returns the average of all the values from the Kernel's section of the image. Max Pooling works as a Noise Suppressant as well.

It removes all noisy activations and conducts de-noising and dimensionality reduction at the same time. Average Pooling, on the other hand, just reduces dimensionality as a noise-suppressing strategy. As a result, we can conclude that Max Pooling outperforms Average Pooling. The ith layer of a Convolutional Neural Network is made up of the Convolutional Layer and the Pooling Layer. Depending on the image complexity, the number of such layers can be expanded even higher to capture even more low-level features, but at the cost of greater processing power. We have successfully enabled the model to understand the features after going through the aforesaid method. After that, we'll flatten the final result and input it to a standard Neural Network for categorization.



(a) Original image

(b) Inverted image

(c) Noise Removal Image

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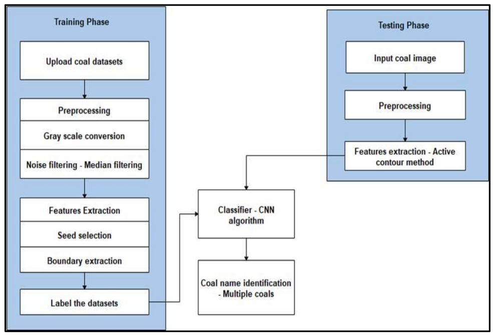
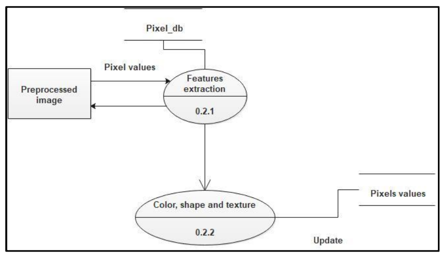
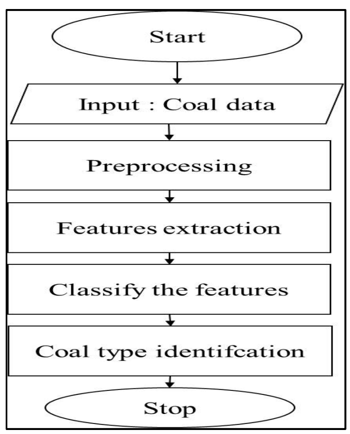
V. SYSTEM ARCHITECTURE



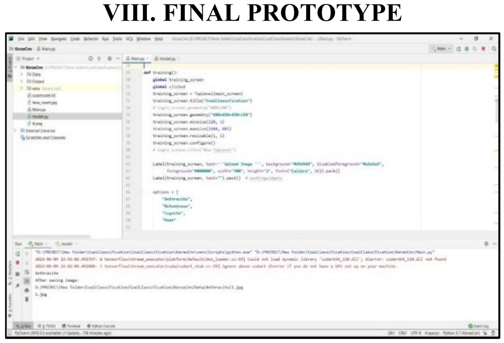
VI. DATAFLOW DIAGRAM



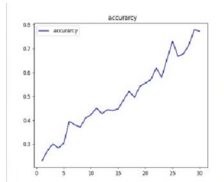
VII. FLOWCHART

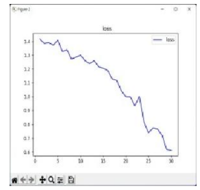


VIII. FINAL PROTOTYPE



DOI: 10.48175/568





IX. RESULT

Our Dataset contains different types of coal and coal gangue. Kaggel contains real time images of coal obtained from mining area. The use of a convolution neural network is used to conduct effective automatic coal categorization in this study. Python is used to carry out the simulation. The precision is calculated and compared to other state-of-the-art approaches. To determine the efficiency of the proposed coal classification scheme, the training accuracy, validation accuracy, and validation loss are determined.

```
import tensorflow as tf

model = tf.keras.models.Sequential([
    # Note the input shape is the desired size of the image 200x 200 with 3 bytes color
    # The first convolution
    tf.keras.layers.Conv2D(16, (3,3), activation='relu', input_shape=(200, 200, 3)),
    tf.keras.layers.MaxPooling2D(2, 2),
    # The second convolution
    tf.keras.layers.Conv2D(32, (3,3), activation='relu'),
    tf.keras.layers.MaxPooling2D(2,2),
    # The third convolution
    tf.keras.layers.Conv2D(64, (3,3), activation='relu'),
    tf.keras.layers.MaxPooling2D(2,2),
    # The fourth convolution
    tf.keras.layers.Conv2D(64, (3,3), activation='relu'),
    tf.keras.layers.MaxPooling2D(2,2),
    # The fifth convolution
    tf.keras.layers.Conv2D(64, (3,3), activation='relu'),
    tf.keras.layers.MaxPooling2D(2,2),
    # Flatten the results to feed into a dense layer
    tf.keras.layers.Flatten(),
    # 128 neuron in the fully connected layer
    tf.keras.layers.Dense(128, activation='relu'),
    # 5 output neurons for 5 classes with the softmax activation
    tf.keras.layers.Dense(4, activation='softmax')
])
```

X. CONCLUSION

To answer the challenge of coal classification, we used feature extraction and neural network technology in this study. The Convolutional neural network approach is proposed, and it is used to create a quick coal categorization model. The CNN algorithm's classification accuracy is higher than that of classic machine learning algorithms, according to experimental results. When compared to the old way of coal classification, our method saves time, is faster, and is more accurate, and has a wide range of practical applications.

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