Coal analysis based on visible-infrared spectroscopy and a deep neural network

Proximate Analysis

Ash (%)

The ash content of coal refers to the remnants after the coal is incompletely burned under the required conditions.

Low heating value (J/g)

The heating value of coal is the heat generated by the complete combustion of the unit mass of coal.

Volatile matter (%)

The volatile matter of coal is the mass defect after coal is heated in the absence of air, which performs the moisture correction under the specified conditions. T

Moisture (%)

Is the colour of the clear sky and the deep sea. It is located between violet and green on the optical spectrum.

Fixed carbon (%)

After we excluded the ash content in the coke button, the residue is called the fixed carbon.

Sulphur (%)

Sulphur is one of the most harmful elements contained in coal. Coal contains a lot of sulphur. Therefore, when it combusts, a lot of SO2 is generated

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The traditional proximate analysis of coal mainly relies on chemical analysis, which is time-consuming and costly. Hence, a method to construct a coal analysis is introduced.

₹350,000

Cost

Of Proximate Analysis using traditional chemical analysis method.

What we Want

Of course, Less cost and more accuracy.

We want:

- Quickly and accurately identify the components of coal
- Decrease analysis costs
- Increase classification efficiency

But How?

DEEP LEARNING

In recent years, deep learning using the convolutional neural network (CNN) has been widely applied in prediction models

Comparison Between Different analysis Method

Traditional Chemical Analysis

- Time= 240 Hours
- Cost= **₹ 350,000**

Using Deep Learning Model

- Time= 10 Hours
- Cost= **₹ 7,000**

Our Plan Of Attack:

- By using the method to analyse moisture (%), ash (%), volatile matter (%), fixed carbon (%), and sulphur (%) contents and the low heating value (J/g). We first obtained different coal sample from different coal areas.
- Then, measured the spectral data through the spectral analysis instrument and extracted spectral features through a convolutional neural network(CNN).

- Finally, we applied the extreme learning machine algorithm(ELM) to construct the prediction and analysis model of the spectral feature data.
- The experimental result shows that the model in the study can predict the components of coal.
- Compared with the chemical analysis method, this method has unparalleled advantages in terms of financial efficiency, speed and accuracy

Our process is easy

Data collection and Processing:

Model Construction

Validation and Result

Data collection and processing

- Spectral data collection (X)

- The determination of the proximate analysis of coal (y)

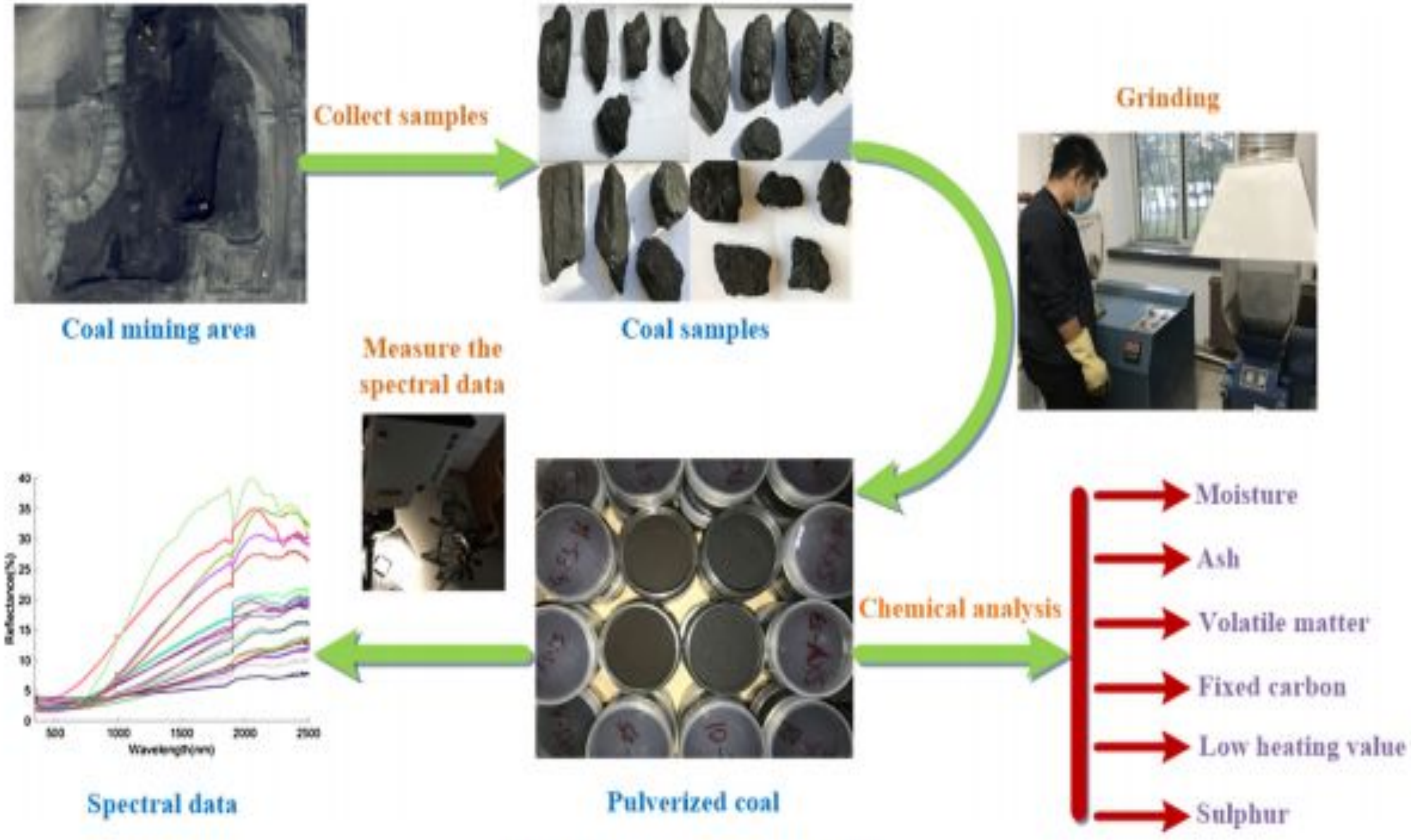


Fig. 1. Data collection experiment.

The model construction

1. Convolutional neural network

    -To extract features

2. Extreme learning machine

    -For Prediction

3. Artificial bee colony algorithm

    -For Weight Optimisation

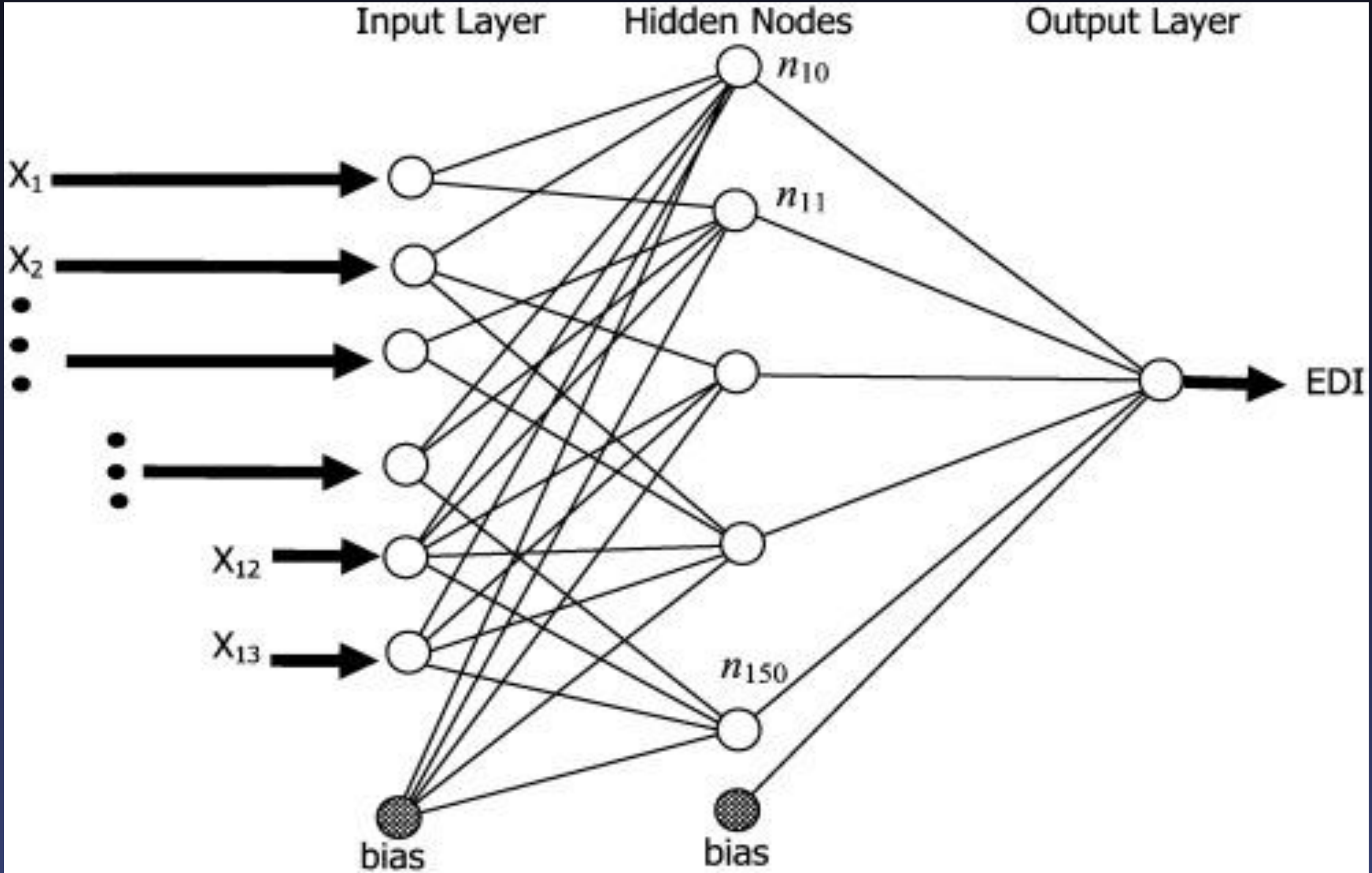
4. Combination of CNN-ELM-ABC

Assumption

1. Spectral data has been generated from Reflectance value of 5 coal Samples
2. We had less data, So data has been generated using Gaussian Noise
3. The Dependant variable is taken from raferance Paper

1.. Architecture Of CNN used for feature extraction:

```
Model: "sequential_3"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_25 (Conv2D)           (None, 72, 72, 32)        4736
_________________________________________________________________
conv2d_26 (Conv2D)           (None, 36, 36, 64)        18496
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 18, 18, 64)        0
_________________________________________________________________
dropout_5 (Dropout)          (None, 18, 18, 64)        0
_________________________________________________________________
conv2d_27 (Conv2D)           (None, 18, 18, 128)       32896
_________________________________________________________________
conv2d_28 (Conv2D)           (None, 18, 18, 256)       131328
_________________________________________________________________
dropout_6 (Dropout)          (None, 18, 18, 256)       0
_________________________________________________________________
conv2d_29 (Conv2D)           (None, 17, 17, 256)       262400
_________________________________________________________________
conv2d_30 (Conv2D)           (None, 16, 16, 128)       131200
_________________________________________________________________
conv2d_31 (Conv2D)           (None, 15, 15, 64)        32832
_________________________________________________________________
conv2d_32 (Conv2D)           (None, 14, 14, 64)        16448
_________________________________________________________________
conv2d_33 (Conv2D)           (None, 13, 13, 64)        16448
_________________________________________________________________
conv2d_34 (Conv2D)           (None, 12, 12, 64)        16448
_________________________________________________________________
conv2d_35 (Conv2D)           (None, 11, 11, 64)        16448
_________________________________________________________________
conv2d_36 (Conv2D)           (None, 10, 10, 64)        16448
_________________________________________________________________
flatten_3 (Flatten)          (None, 6400)              0
=================================================================
Total params: 696,128
Trainable params: 696,128
Non-trainable params: 0
```


Input Layer
Hidden Nodes
Output Layer
n_{10}
n_{11}
n_{150}
X_1
X_2
X_{12}
X_{13}
EDI
bias
bias

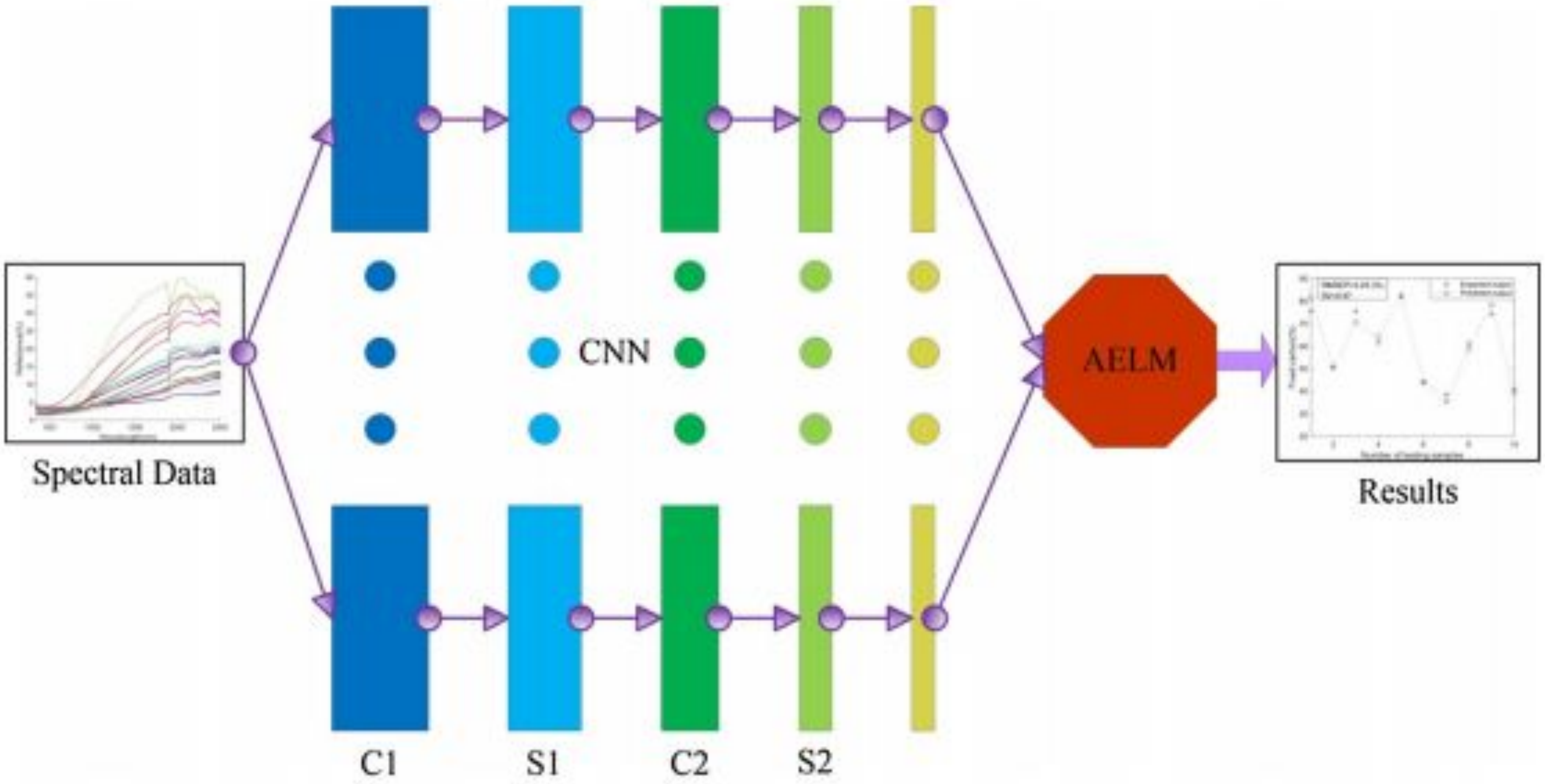


Fig. 2. The CNN-AELM proximate analysis model of coal.

Validation and result

To examine the effectiveness of this method, the evaluation criteria of the model's performance, We took

1. coefficient of determination of prediction (R2p)

2. cross validation(R2c)

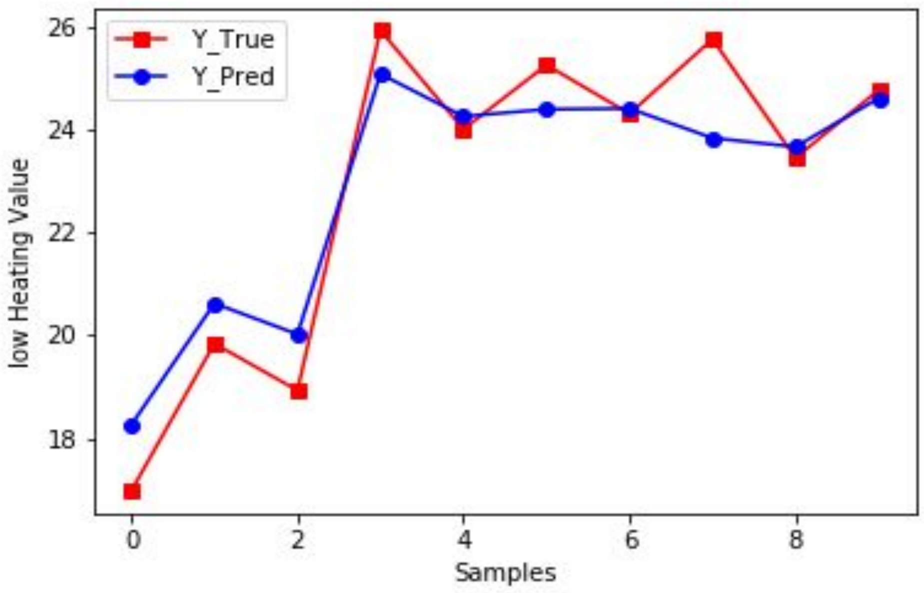
The value range of R2p and R2c are between [0, 1]. The closer R2p and R2c are to 1

3.Root-mean-square error of prediction (RMSEP)

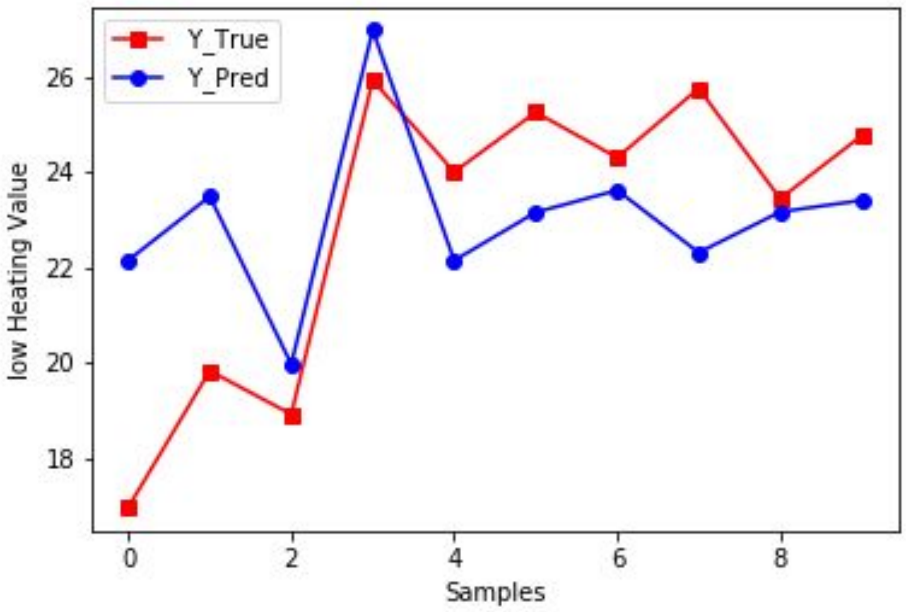
4. Cross validation (RMSECV)

Smaller the value of RMSEP and RMSECV are, the better the model performs

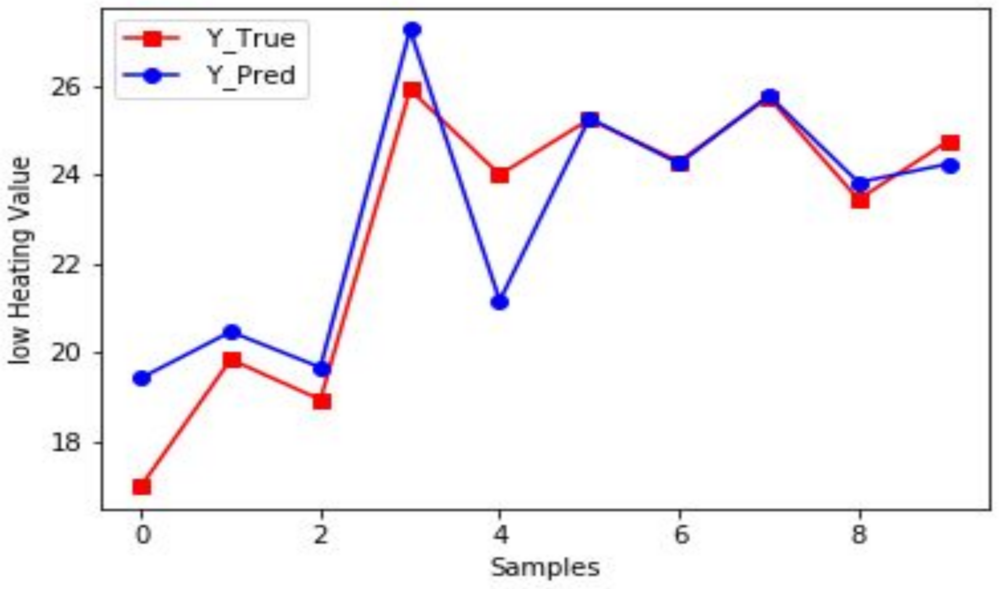
CNN-Random Forest



CNN-SVM



CNN_ELM



Model and Validation

CNN-Random Forest

R2_score= 0.864990

Mean Square root error= 1.095819

CNN-SVM

R2_score= 0.572226

Mean Square root error= 1.950575

CNN-ELM

R2_score= 0.880949

Mean Square root error= 1.029016

Conclusion

- The result illustrated that the CNN-ELM network can well predict the industrial indexes of coal. The CNN can better extract the features of spectral data.
- The CNN and ELM network can compensate for each other's respective disadvantages when combined and can construct a better analysis model.

Thanks!

Any questions?

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